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The commodity future investment with the impact of
Chinese specific factors

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Supervisors: Dr. Jing-Ming Kuo and Prof Rob Dixon

A Dissertation Submitted for the Degree of Doctor of Philosophy

Abstract

This thesis explores the commodity futures investment strategy with the impact of the Chinese specific factors. First, I study the so called Chinese specific factors. To do so, I investigate how commodity future price interacts with domestic macroeconomic variables and overseas futures prices respectively. Specifically, Chapter 2 emphasizes the interaction between domestic commodity futures prices and domestic macroeconomic variables such as interest rates, monetary growth, exchange rates and industrial growth. Among these variables, monetary growth should receive deeper attention because it is widely regarded as the main channel of monetary policy transmission. Subsequently, Chapter 3 focuses on the interaction between domestic commodity futures prices and overseas commodity futures prices. Having gained a clear understanding of the Chinese specific factors, a dynamic timing strategy is accordingly proposed in chapter 4.

Chapter 2 is primarily focused on the interaction between domestic macroeconomic variables and domestic commodity future price movement. Specifically, I try to explore whether low (high) interest rates, loose (tight) money supplies, low (high) foreign exchange rates (Renminbi / US Dollar rate) and high (low) economic growth will lead to high (low) commodity prices and whether commodity prices present overshooting behaviour in response to the interest rate, money supply or changes in the foreign exchange rate. It has been argued by Frankel (1986, 2006) that commodity prices tend to overshoot in response to interest rates as well as to changes in the exchange rates based on Dornbusch's (1976) model. Evidences from the SVAR models show that part of the theory regarding the relationship between macroeconomic variables and commodity price movement can be supported. The empirical also results suggest that the commodity price shock itself make the largest contribution to commodity price shocks in general. An interest rate shock barely contributes while an M1 growth shock contributes substantially in metals. Foreign exchange rate shocks contribute approximately 40 percent to some commodities,

while industrial output shocks comprise approximately 20 to 30 percent to some metals.

In chapter 3, the thesis tries to explore the impacts between China's futures market and overseas futures markets in chapter 3. Research from this angle could help reveal which side has stronger pricing power. Specifically, I aim to study the information spillover effect between the domestic spot and futures market as well as the information and risk spillover effects between the domestic metal futures market and the overseas metal futures market. Moreover, to check whether China has gained pricing power in the global commodities market, I also study the risk spillover effect between the domestic metal futures market and other overseas financial markets. From the empirical evidences in Chapter 3, it could be seen that asymmetry factors are significant in the futures market, no matter in the Chinese market or overseas market. The empirical results of Granger causality test in Chapter 3 show that movement in the SHFE market could directly guide movement in the LME market, indicating a rise in China's pricing power in the global commodity market. However, such pricing power is limited and should not be wildly exaggerated.

Chapter 4 forms an effective dynamic timing strategy in China's commodity market with full consideration of the Chinese specific factors. I adopt Vrugt, Bauer and Molenaar's (2004) dynamic modeling approach to predict the sign of monthly returns for the three metal futures listed on the Shanghai Futures Exchange: copper, aluminum and zinc. Following Vrugt, Bauer and Molenaar (2004), the base set of explanatory variables is classified into three categories: 1) business cycle indicators; 2) monetary environment indicators; 3) indicators of market sentiment. The empirical results in Chapter 4 show that the timing strategy can offer better returns, a lower standard deviation and, as a consequence, a higher information ratio for all three metal futures.

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Chapter 1

Introduction

Recently, Chinese specific factors have become a hot term in the global commodity market. Prior to the global financial crisis in 2008, China appeared to be a complete “loser”. For example, a spokesman from the Ministry of Commerce confessed in a press conference that when China bought something, its price would go up, and when China sold something, its price would go down. Governments, academia and the public were concerned about this tendency. Then the global financial crisis, triggered by the bankruptcy of Lehman Brothers, hit the world economy heavily. China’s economy also faced a serious shock because global demand rapidly evaporated. Following the launch of an unprecedented 4 trillion stimulus package, a V-shaped recovery has been witnessed in China and in the rest of the world. The global commodity market has also been strongly boosted. During this recovery, China has gradually become a “winner” in the global commodity market. China’s fiscal, monetary and industrial policy appears to have an increasing impact on the market, and one can wonder whether Chinese specific factors actual do have such major influences.

Commodity futures investing is a well-studied topic in academia because much extensive empirical evidence (Abanomey and Mathur (2001), Georgiev (2001), Kaplan and Lummer (1998)) has shown that commodities serve as good diversifier when added to the traditional asset portfolio. Due to the low correlation of commodities with traditional assets, overall risk is reduced while no (or a less-than-proportional) return is sacrificed. Investment strategies, such as dynamic timing (Vrugt, Bauer and Molenaar’s (2004)), have been proposed to take advantage of the excellent characteristics presented by commodities. Empirical results from developed countries have demonstrated that investors can profit from adopting these

strategies. It is thus natural to ask whether these strategies could also deliver superior performance in developing countries such as China.

In this study, I explore the commodity futures investment strategy considering the impact of Chinese specific factors. First, I study the so-called Chinese specific factors. To do so, I investigate how commodity futures prices interact with domestic macroeconomic variables and overseas futures prices. Specifically, Chapter 2 emphasizes the interaction between domestic commodity futures prices and domestic macroeconomic variables such as interest rates, monetary growth, exchange rates and industrial growth. Among these variables, monetary growth should receive deeper attention because it is widely regarded as the main channel of monetary policy transmission. Subsequently, Chapter 3 focuses on the interaction between domestic commodity futures prices and overseas commodity futures prices. Having gained a clear understanding of the Chinese specific factors, a dynamic timing strategy is accordingly proposed in chapter 4.

Chapter 2 is primarily focused on the interaction between domestic macroeconomic variables and domestic commodity futures price movements. Specifically, I try to explore whether low (high) interest rates, loose (tight) money supplies, low (high) foreign exchange rates (Renminbi / US Dollar rate) and high (low) economic growth will lead to high (low) commodity prices and whether commodity prices present overshooting behaviour in response to the interest rate, money supply or changes in the foreign exchange rate. It has been argued by Frankel (1986, 2006) that commodity prices tend to overshoot in response to interest rates as well as to changes in the exchange rates based on Dornbusch's (1976) model. Based on the literature, an empirical test will be conducted in the context of China.

Fan, Yu and Zhang (2010) claimed that quantitative tools (including adjusting the required reserve rate, open market operation, window guidance and credit rationing) have played a more active role than price tools (setting base interest rates) in China in

responding to both the inflation rate and real output. I will therefore check the overshooting behaviour of commodity prices in response to monetary growth in particular. Moreover, I will also examine the possible contribution of China's economic growth to the prices of other commodities. Svensson (2006) argued that an adequate account of the contribution of world economic growth in particular is required as this may lead to both higher interest rates and higher commodity prices. Akram (2009) found that negative shocks to world economic activity lead to lower real interest rates and commodity prices. Shocks to world economic activity are found to account for a large share of the fluctuations, particularly in oil and metal prices. Here, I will check whether this also holds in China's case.

The data for conducting the empirical test in Chapter 2 is from the Chinese financial database – the Wind system. All of the data used is stylized in month terms. The commodity futures prices (including three metals: aluminium, copper and zinc and three agricultural products: beans, cotton and wheat) are in the form of an index. Interest rates and foreign exchange rates are in nominal form. Monetary growth figures are generated from the year-on-year growth of the broad money supply and the narrow money supply (M2 and M1, respectively). Economic activities figures are generated from the year-on-year growth of industry added value. The data basically range from 1998.1 to 2010.12 with the exceptions of cotton (cotton futures contracts started in 2004.6), zinc (zinc futures contracts started in 2007.3) and foreign exchange rates (the floating exchange rate could be obtained starting in 2006.1).

To empirically test the hypotheses above, I first apply the Granger causality test. This test found that most of the null hypotheses could not be rejected. Subsequently, I use Structural Vector Auto Regression (SVAR) models. SVAR models will, after the appropriate identification of shock structures, allow us to examine the response of commodity futures prices to unanticipated shocks, particularly to interest rates and the CNY/USD exchange rate, while taking into account the dynamic interaction between commodity futures prices and macroeconomic variables. The standard Choleski

scheme will be relied upon to identify the shock structures according to common practice.

Evidences from the SVAR models show that part of the theory regarding the relationship between macroeconomic variables and commodity price movement can be supported. A negative relationship between interest rates and commodity prices can be shown only for zinc, while the positive “overshooting” between the interest rate and commodity prices, the so-called “shock dependence”, has been observed between the inter-bank repo rate and aluminium (copper) prices, between the exchange repo rate (average rate) and bean prices. As expected, a positive relationship between monetary growth and commodity prices can be found for several commodities with statistical significance. This demonstrates that monetary growth (the credit channel) plays a bigger role than the interest rate channel in promoting commodity prices in China.

In chapter 2, I also find that a sudden shock in the foreign exchange market prompts a positive response in some commodity prices. However, it might be more appropriate to state that the foreign exchange rate plays a minor role in commodity price movement because the foreign exchange rate’s movement is unidirectional. Meanwhile, it could be found that output shocks could lead to dramatic responses in some commodity prices.

Chapter 2 also adopts forecast error variance decompositions (FEVD) to investigate the contribution of different structural shocks to fluctuations in the modelled variables. The empirical results suggest that the commodity price shock itself make the largest contribution to commodity price shocks in general. An interest rate shock barely contributes while an M1 growth shock contributes substantially in metals. Foreign exchange rate shocks contribute approximately 40 percent to some commodities, while industrial output shocks comprise approximately 20 to 30 percent to some metals.

Subsequently, the thesis tries to explore the impacts between China's futures market and overseas futures markets in chapter 3. Research from this angle could help reveal which side has stronger pricing power. Specifically, I aim to study the information spillover effect between the domestic spot and futures market as well as the information and risk spillover effects between the domestic metal futures market and the overseas metal futures market. Moreover, to check whether China has gained pricing power in the global commodities market, I also study the risk spillover effect between the domestic metal futures market and other overseas financial markets.

From the literature consulted, I found that works on the relationship between the futures market and the spot market focus mainly on price discovery, and little research has been done on information spillover between the spot and futures markets and between the domestic and overseas futures markets, particularly the metal futures market in China. Hong and Cheng (2005) studies information spillover between China's domestic stock market and the global equity market. However, vital differences exist between the stock market and the futures market. One of the most significant differences is that short selling in stock is forbidden in China, meaning that a long position faces downside risk but no upside risk. This is definitely not the case in the futures market: heavy usage of leverage and margin calls is common practice in China's futures market. Thus it will be necessary to make specific adjustments to study risk spillover in China's futures market.

Liu, Cheng, Wang, Hong and Li (2008) represents an up-to-date piece of research in my research field. This work takes the upside risk into account (the short-seller's risk) rather than merely focusing on the downside risk. A more complicated research framework – using a kernel-based Granger causality test - has been proposed in place of the previously applied simplified linear Granger causality test. However, Liu, Cheng, Wang, Hong and Li (2008) merely explore the information spillover between the domestic spot and futures markets; no attention has been given to cross-border

information spillover. Moreover, the dataset in use includes through the middle of 2006. The inability to take more recent data (especially the data range including the global financial crisis) may not help to reveal changes in China's pricing power in the global commodity market, especially after the global financial crisis in 2008.

To detect the cross-border spillover effect, I must ensure that the domestic futures market functions properly and effectively. In other word, the interaction between the domestic spot and futures markets should work in both directions, with the futures market playing the leading role. After checking the function of the domestic futures market, I will test whether the domestic futures market could have an impact on the global futures market. Moreover, I will examine whether the risk spillover effect exist between the Chinese domestic futures market and other overseas financial markets (whether it has an extensive risk spillover effect).

The empirical test in chapter 3 is conducted in three steps. First, I choose the appropriate GARCH model to describe the volatility patterns of the time series. In particular, TGARCH models have been chosen for all of the financial time series that share the characteristic of allowing short selling. These models can help us to detect whether information asymmetry exists. Second, I compute both the upside and downside risk by adopting the Value-at-Risk (VaR) model. In particular, both upside and downside VaR are taken into account for all of the financial time series that share the characteristic of allowing short selling. In this step, backtesting is conducted to check whether the VaR model can deliver satisfactory results – a low percentage of the sample cross the upside and downside VaR. Finally, the Granger causality test is conducted to detect whether information spillover exists across markets. Specifically, this test is conducted considering three perspectives: 1) information spillover and risk spillover effects between the Chinese domestic metal spot and futures markets; 2) information spillover and risk spillover effects between Chinese and overseas metal futures markets; 3) the information spillover and risk spillover effects between the Chinese metal futures market and overseas financial markets.

The data used in chapter 3 range from 1995.4.17 to 2010.12.31, containing 3814 daily observations. The data for conducting the empirical test are taken from the Chinese financial database – the Wind system. All of the data used are stylized in daily terms. Copper is studied for spot futures interactions; the Shanghai Futures Exchange (SHFE) and London Metal Exchange (LME) aluminium, copper and zinc futures are studied for cross-commodity market futures interactions; the Australian dollar- US dollar (AUDUSD) foreign exchange rate and the Australian stock index (ASX) are studied for cross-financial market interaction.

From the empirical evidences in Chapter 3, it can be seen that asymmetry factors are significant in futures markets, regardless of whether we are examining China's market or oversea markets. In the Chinese metal futures market, the sign of the asymmetry factor is positive for copper and zinc futures while negative for aluminium futures. Therefore, although the mechanism of buying and selling is symmetrical in the futures market, both good news and bad news still have an asymmetric impact on market volatility. For copper and zinc futures, the impact of bad news is greater; for aluminium, the impact of good news is greater. In the Chinese futures market, people prefer to take long positions in speculative copper and zinc products due to psychological factors (Liu, Cheng, Wang, Hong and Li, 2008). When futures prices increase, the number of speculators also grows. With risk growing, the reaction to market uncertainty becomes stronger. As for aluminium, excessive supply will dampen its price for a long period of time. It is probable that any goods news could lead to a moderate rebound in price. The sign of the asymmetry factor is different in the LME market, however: it is positive only for copper and negative for both aluminium and zinc. The results show that the impact of good and bad news on market volatility is also asymmetric. A closer watch could tell that the sign of the asymmetry factor is identical for both aluminium and copper in the SHFE and the LME. Meanwhile, it can be seen that asymmetry factors are significant in the AUDUSD time series and that the sign of the factor is positive, indicating that the

impact of bad news is greater than that of good news for AUDUSD.

The empirical results of the Granger causality test in Chapter 3 support some of the proposed hypotheses. Specifically, the results indicate that in China's domestic metal market, futures pricing functions quite well because a two-way causal link is found to exist between spot and futures products, indicating that the price discovery function performs effectively and steadily in China. As for the interaction between the domestic and overseas futures markets, a causal link does exist from the SHFE market to the LME market; this result also holds for the extreme upside and downside scenarios. To some extent, this finding shows that movement in the SHFE market could directly guide movement in the LME market, indicating a rise in China's pricing power in the global commodity market. As for the interaction between the SHFE metal market and overseas financial markets, no consistent conclusions were found, indicating that the Chinese specific factor may have limited impact on the global financial market as a whole.

In chapters 2 and 3, I investigate how commodity futures prices interact with domestic macroeconomic variables and overseas futures prices. The findings lay a good foundation for my goal in chapter 4: forming an effective dynamic timing strategy in China's commodity market with full consideration of Chinese specific factors.

According to Abanomey and Mathur (2001), Georgiev (2001), and Kaplan and Lummer (1998), commodities serve as good diversifiers when added to a traditional asset portfolio. Edwards and Caglayan (2001) have shown that commodity funds have higher returns during bearish stock markets along with a lower correlation. Meanwhile, Pesaran and Timmermann (1995) and Bauer, Derwall and Molenaar (2004) have shown that well-specified dynamic timing strategies can generate better performance than a pure "buy-and-hold" strategy for some assets, such as stocks. Hence, it is natural to ask whether a dynamic timing strategy could beat the "buy-and-hold" strategy for commodity futures in China.

In chapter 4, I adopt Vrugt, Bauer and Molenaar's (2004) dynamic modelling approach to predict the sign of monthly returns for the three metal futures listed on the Shanghai Futures Exchange: copper, aluminium and zinc. Following Vrugt, Bauer and Molenaar (2004), the base set of explanatory variables is classified into three categories: 1) business cycle indicators; 2) monetary environment indicators; 3) indicators of market sentiment.

These three categories have been used predominantly in studies investigating the relationship between the macroeconomy and traditional asset classes or in timing studies, such as Pesaran and Timmermann (1995). However, this type of research framework has not been well applied to non-traditional asset classes, such as commodity futures, let alone commodity futures in China. Here, the variables in each category should be collected with full consideration of "Chinese specific factors". Consequently, my findings from the two previous chapters offer great help. As for the data, they are taken from the Chinese financial database – the Wind system. All of the series are stylized in monthly terms. Due to concerns related to availability and practicality, all of the independent variables are lagged by one month.

Econometrically, this approach involves a recursive estimation procedure that allows for continuous permutations among the determinants in accordance with a predefined model selection criterion. During the in-sample period, I estimate parameters for these models using standard Ordinary Least Squares (OLS). Following this procedure, each model generates monthly signals during a 12-month training period. Then, at the end of the training period, I rank all models by the realized information ratios. The strategy with the highest realized information ratio is used to forecast the sign of next month's metal futures return. Finally, in the out-of-sample trading period, futures on the metal futures market are bought or sold depending on the signal.

The empirical results in Chapter 4 show that the timing strategy can offer better

returns, a lower standard deviation and, as a consequence, a higher information ratio for all three metal futures. The strategy works especially well for zinc futures: it recorded a 2.53% return (an excess return of 2.57%) and lowers the standard deviation by more than 1%, leading to a much better IR ratio. The hit ratio, defined as the percentage of correctly predicted signals, is above 50% for all three products. According to the Henriksson-Merton (1981) non-parametric market-timing test, the active strategy possesses significant timing skill at a 5% level of significance. Clearly, the “buy-and-hold” strategy takes long positions 100% of the time, whereas the active strategy varies positions. It takes approximately 30% long positions for copper and less than 10% long positions for aluminium. For zinc, it takes half long positions and half short positions.

In Chapter 4, the results also indicate that the factor inclusion does vary across the entire sample period for all three metals. For aluminium, the variable exchange rate and the lagged LME aluminium returns are included over the entire period. The results indicate that domestic aluminium is highly correlated to the global market. For copper, the factor inclusion appears to be comparatively irregular and inconsistent. All six variables are included during the out-of-sample period. For zinc, only four of the six variables are included; monetary growth and inflation variables are excluded. The lagged stock return index and lagged LME zinc return variable are included over the entire period. The result shows that zinc futures are quite speculative and highly influenced by global markets. Furthermore, concerns about economic intuition do not pose a problem.

The thesis extends knowledge about commodity futures investment in the following ways. First, the so-called Chinese specific factors in China’s commodity market are studied systematically. Chapter 2 investigates the interaction between macroeconomic variables and commodity futures price movement. Chapter 3 explores the impacts between China’s futures market and overseas futures markets. Second, all of the tests are conducted on the Chinese commodity futures market, a hot topic that has only

rarely been thoroughly studied with traditional approaches. Well-specified approaches such as the overshooting model, information spillover and risk spillover have been widely used in developed markets; applying them in China's market fills this research gap.

Third, China's commodity pricing power is empirically tested while checking the information and risk spillover effect between the domestic metal futures market and overseas metal futures markets. Moreover, extensions are made to check between the domestic metal futures market and overseas financial markets. Finally, a dynamic timing strategy based on understanding Chinese specific factors is proposed. Fresh empirical results further demonstrate that commodity futures as a non-traditional asset can also deliver superior returns in China.

Chapter 2

Commodity prices, monetary liquidity and foreign exchange rates – an empirical test of the overshooting theory in China

2.1 Introduction

This chapter is mainly focused on the interaction between macroeconomic variables and commodity futures price movements. Specifically, I try to explore whether low (high) interest rates, a loose (tight) money supply, low (high) foreign exchange rates (Renminbi / US Dollar rate) and high (low) economic growth will lead to high (low) commodity prices and whether commodity prices present overshooting behaviour in response to interest rates, the money supply and changes in the foreign exchange rates. It has long been argued by Frankel (1986, 2006) that commodity prices tend to overshoot in response to interest rates and changes in exchange rates based on Dornbusch's (1976) model. Based on these studies, an empirical test will be conducted in the context of China. Fan, Yu and Zhang (2010) claimed that quantitative tools (including adjusting the required reserve rate, open market operations, window guidance and credit rationing) have played a more active role than price tools (setting base interest rates) in China in responding to both the inflation rate and real output. Therefore, I will check the overshooting behaviour of commodity prices in response to monetary growth in particular. Moreover, I will also examine the possible contribution of China's economic growth to the prices of other commodities. Svensson (2006) argued that an adequate account of the contribution of world economic growth in particular is required as it may lead to both higher interest rates and higher commodity prices. Akram (2009) found that negative shocks to world economic activity lead to lower real interest rates and commodity prices. Shocks to world economic activity are found to account for a large share of the fluctuations in

oil and metal prices in particular. Here, I will also check whether these findings hold in China's case.

The contribution of this chapter is that it checks whether the overshooting model holds in the context of China's market, as no previous research has been conducted in this regard. In applying the overshooting model, full consideration of Chinese monetary variables allows insightful observations about the interaction of these variables and commodity price movements.

The data for conducting the empirical tests are from the Chinese financial database – the Wind system. All of the data used are stylized in month terms. The commodity futures prices (including three metals: aluminium, copper and zinc and three agricultural products: beans, cotton and wheat) are in the form of an index. Interest rates and foreign exchange rates are in nominal form. Monetary growth figures are generated from the year-on-year growth in the broad money supply and the narrow money supply (M2 and M1, respectively). Economic activity figures are generated from the year-on-year growth of industry added value. The data range from 1998.1 to 2010.12 with the exceptions of cotton futures contracts started in 2004.6), zinc (zinc futures contracts started in 2007.3) and foreign exchange rates (the floating exchange rate could be obtained starting in 2006.1).

To empirically test the hypotheses above, I first apply a Granger causality test. I found that most of the null hypotheses could not be rejected. Subsequently, I use Structural VAR (SVAR) models. After the appropriate identification of shock structures, SVAR models will allow us to examine the response of commodity prices to unanticipated shocks, in particular to interest rate and the CNY/USD exchange rate shocks, while accounting for the dynamic interaction between commodity prices and macroeconomic variables. The standard Choleski scheme will be relied upon to identify the shock structures according to common practice.

Evidence from the impulse response functions shows that part of the theory regarding the relationship between macroeconomic variables and commodity price movements can be supported. A negative relationship between interest rates and commodity prices can be supported for some metals. A positive relationship between monetary growth and commodity prices can be supported for several commodities with statistical significance. These results demonstrate that monetary growth (the credit channel) plays a bigger role than the interest rate channel in promoting commodity prices in China. I also find that some commodity prices overreact to output shocks.

The forecast error variance decompositions (FEVD) suggest that the commodity price shock itself makes the biggest contribution to commodity price shocks in general. The interest rate shock hardly makes a contribution, while M1 growth shocks contribute substantially to metals. Foreign exchange rate shocks contribute approximately 40 percent to some commodities; industrial output shocks contribute approximately 20 to 30 percent to some metals.

The rest of this chapter is organized as follows: section 2.2 presents the consulted literature. Section 2.3 provides a description of the variables used, the descriptive statistics for their data series and the methodology adopted. Estimation and empirical results are presented in section 2.4. Finally, section 2.5 concludes the chapter.

2.2 Literature Review

2.2.1 The Overshooting Model

2.2.1.1 Commodity prices overshooting in response to interest rates

Dornbusch (1986) developed a theory of exchange rate movements under the assumptions of perfect capital mobility, a slow price adjustment of goods markets relative to asset markets, and consistent expectations. He derived a perfect foresight path, and it has been shown that along that path, monetary expansion causes the

exchange rate to depreciate. An initial overshooting of exchange rates (reflected in depreciation beyond that under the equilibrium state) is shown to derive from the differential adjustment speeds of markets. The magnitude and persistence of the overshooting is developed in terms of the structural parameters of the model. To the extent that output responds to a monetary expansion in the short run, this has a dampening effect on exchange depreciation and might, in fact, lead to an increase in interest rates. Specifically, if real output is fixed, a monetary expansion will, in the short run, lower interest rates and cause the exchange rate to overshoot its long-run depreciation level. If output, on the contrary, responds to aggregate demand, the exchange rate and interest rate changes will be dampened. While the exchange rate will still depreciate, it may no longer overshoot, and interest rates may actually rise.

Frankel (1986) applied the Dornbusch overshooting model to study the impact of monetary policy on agricultural commodity prices. He argued that a decline in the nominal money supply could be understood as a decline in the real money supply in the short run. An increase of the real interest rate as a consequence of a tightened money supply would cause a decrease in real commodity prices. Commodity prices overshoot their new equilibrium (in other words, commodity prices will experience a proportionately greater fall than the money supply) so that an expectation could be generated that futures appreciation would be sufficient to offset the higher interest rate. As the general price level rises over time, the reduction in the real economy and its effect on the real interest rate and real commodity prices also wanes. Frankel (1986) also noted that a decline in the money growth rate would also result in commodity prices overshooting.

Frankel (2006) studied that connection between monetary policy and agricultural and mineral commodities. The author conducted empirical tests on the US and then on smaller countries to test the claim that low real interest rates would lead to high real commodity prices. Supported by empirical results, the author found that one probable channel for this effect is that higher interest rates may dampen the desire to carry

commodity inventories.

Boschi (2009) argued that the overshooting phenomenon should be attributed to the higher speed of adjustment for agricultural and mineral prices compared to most other prices: in many non-ferrous metals industries, producers and consumers sign annual contracts specifying quantities and grades. He specified a theoretical framework based on a Cournot competition that modelled the market behaviour of aluminium to test the overshooting theory in the world aluminium market. Incorporating incomplete adjustments to shocks occurring near the delivery date of futures contracts, the author aimed to discover a probable high persistence in the aluminium spot price. The empirical results indicated that the impact of the real interest rate on the aluminium price is small, although statistically significant.

Svensson (2006) argued that an adequate account of the contribution of world economic growth in particular is required, as it may lead to both higher interest rates and higher commodity prices. In other words, the relationship between real interest rates and commodity prices is likely to be shock dependent. Therefore, a positive relationship between real interest rates and commodity prices may emerge due to simultaneity bias if the interest rate is not treated as an endogenous variable.

2.2.1.2 Commodity prices overshooting in response to the foreign exchange rate

Ridler and Yandle (1972) originally built a simplified model for analysing the effects of exchange rate changes on the prices of primary commodities. Real appreciation of the US dollar with currencies of other countries may immediately lead to an increase in the local relative prices of commodities in other countries if they are unable to maintain purchasing power parities. Therefore, the foreign demand for commodities would decline and the foreign supply would rise, leading to a decrease in commodity prices in world commodity markets. Similarly, real depreciation of the US dollar may

result in an increase in world commodity prices.

Hua (1998) used quarterly data for 1970 q2–1993 q3 with the application of the cointegration technique to test the hypothesis of a long-run quantifiable relationship between non-oil primary commodity prices and macroeconomic variables. The author reached the conclusion that cointegration existed between commodity prices and the real effective exchange rate of the dollar.

Hamilton (2008) revealed the negative relationship between the value of the dollar and prices of commodities denominated in dollars. The negative relationship followed from the law of one price for tradable goods. A decline in the value of the dollar, accordingly, must be outweighed by an increase in the price of commodities denominated in dollars and/or a fall in their foreign currency prices to ensure the same price when measured in dollars. In addition, because many commodities are priced in dollars in international markets, a weaker dollar may increase the purchasing power and commodity demand of foreign consumers, while reducing the returns of foreign commodity suppliers and their supplies. If the demand or supply of commodities is relatively price inelastic, which is generally believed to be the case for many commodities, especially crude oil, the price impact of shifts in the demand and supply of commodities may be particularly large.

2.2.1.3 The impact of economic activity on commodity prices

Cooper and Lawrence (1975) discovered that economic activities are generally considered to be a major factor in non-oil primary commodity demand. An increase in industrial production will directly boost demand for raw materials such as metals, minerals, and agricultural products as intermediate inputs and will indirectly boost the demand for food and tropical beverages as final consumption items through the consequent increases in incomes. However, scholars have had doubts about the

hypothesis that economic activities have permanent effects on prices. Ramanujam and Vines (1990) showed large short-run effects from the industrial production of developed countries on the prices of primary commodities as well as small significant permanent effects.

Using quarterly data for 1970 q2 – 1993 q3 with the application of the cointegration technique, Hua (1998) tested the hypothesis of a long-run quantifiable relationship between non-oil primary commodity prices and macroeconomic variables. The author found that cointegration exists between commodity prices and economic activities.

Labys, Achouch and Terraza (1999) applied dynamic factor analysis to determine the impact of macroeconomic influences on LME metal prices. They adopted five macroeconomic variables including industrial production, consumer prices, interest rates, stock prices, and exchange rates to test the response of metal prices. The empirical results confirmed a strong relationship between international business cycles and the estimated common factor in metal price cycles. Nevertheless, the influences of macroeconomic variables other than industrial activity appeared to be much lower.

Bhar and Hamori (2008) empirically examined the information content of commodity futures prices for monetary policy. They used the cross-correlation function approach to empirically analyse the relationship between commodity futures prices and economic activities (for example, consumer prices and industrial production) between 1957.1 and 2005.2. Moreover, the empirical results also showed that commodity prices could serve as information variables for monetary policy not only in mean, but also in variance.

2.2.2 The financial market in China

2.2.2.1 Monetary policy in China

Fan, Yu and Zhang (2010) investigates the responsiveness of the Chinese

government's monetary policies in terms of the money supply and interest rates to economic conditions and the effectiveness of these policies in achieving the goals of stimulating economic growth and controlling inflation. They analyse the responsiveness and effectiveness by estimating the Taylor rule, the McCallum rule, and a vector autoregressive model using quarterly data for the period 1992-2009. The results indicate that, overall, the monetary policy variables respond to economic growth and the inflation rate, but the magnitudes of the responses are much weaker than those observed in market economies. The money supply responded actively to both the inflation rate and the real output and had certain effects on the futures inflation rates and real output. Official interest rates, on the other hand, responded passively to the inflation rate and did not respond to the real output. Official interest rates also do not have any effect on futures inflation rates or real output.

2.2.2.2 Interest rates and monetary growth in China

China regulated savings rates until the mid-1980s. Due to the short history of China's market economy and the attention given to developing the stock market, the Chinese bond market and interest rate liberalization are underdeveloped. China's spot interest rate is determined in two main markets: the inter-bank borrowing/offering market and the bond repurchase market. Chinese inter-bank borrowing/offering markets appeared in the 1980s at different locations over China and were united into a single market in 1996.1 with "CHIBOR" as its uniform rates. CHIBOR mainly consists of short-term interest rates, with four months as the longest maturity. On 2007.1.4, the Chinese inter-bank borrowing/offering centre located in Shanghai began to report the Shanghai inter-bank offered rate, which is called SHIBOR. CHIBOR and SHIBOR primarily characterize China's short-term interest rates.

Chinese collateralized bond repurchases began in 1991 at four stock exchanges. (Shanghai, Wuhan, and Tianjin together with the STAQ system) In 1997, to prevent banks from entering into stock markets, the Chinese central bank, the People's Bank of China, prohibited all commercial banks from collateralized bond repurchases on

stock exchanges and opened another bond repurchase sub-market within the inter-bank market. This led to two independent and segmented bond repurchase markets in China: the OTC market at inter-bank markets and the electronic market at stock exchanges. These two markets are artificially segmented, with different prices for the same bond.

The long-term interest rates are determined by China's long-term bond market. There are also two segmented long-term bond markets, the OTC bond market at the inter-bank market and the electronic market at stock exchanges. The interest rates of middle maturities are controlled tightly by the Chinese central bank. They do not change every day to reflect market information but remain unchanged for a relatively long period, changing only when the Chinese government uses them as an instrument of interest rate policy.

There are two main deficiencies in the current interest rate mechanism in China that hinder its fundamental roles in the Chinese economy. First, there exist two independent bond markets that share similar functions and trade the same products, i.e., the inter-bank OTC market and the exchange electronic market. Because they are artificially segmented, the same bond has different prices at these two markets, resulting in two different interest rates between the inter-bank market and the exchange market. The difference in the interest rate levels of the two segmented markets reflects different investor expectations. It is very difficult, if not impossible, to develop derivative markets without a uniform market interest rate. Second, the deposit rates in China are still heavily regulated by the Chinese central bank. They cannot be changed by commercial banks to reflect market information. Therefore, there is a large gap between the regulated deposit rates and the market interest rates, and serious problems and arbitrage opportunities can arise (Lin and Zheng, 2004).

Fan and Zhang (2006) stated that the inter-bank repo market in China has provided the best information about market-driven short-term interest rates since its inception

due to the lack of short-term government bonds. They examined the behaviour of the repo rates of various terms and their term premiums. It is found that the pure expectations hypothesis is statistically rejected, although the term premiums are economically small. It is shown that the short-term repo rate, repo rate volatility, repo market liquidity, and repo rate spreads are all important in determining the term premiums.

Fan and Chu (2007) compared China's exchange-traded and inter-bank-traded repo markets with identical products but different interest rates. For the sample period of 2000.1 through 2005.12, the apparent difference across the two markets is not arbitrated away due to market segmentation. When the sample period is divided into two halves, however, they see striking differences between the two. In the first half, the differences between the exchange repo rates and the inter-bank repo rates are positive on average and the standard deviations of the differences are large. However, the cross-market repo rate differences in the second half of the sample period are on average near zero, with standard deviations only slightly smaller than those in the first half. In addition, the cross-market repo rate differences exhibit much stronger persistence in the first half of the sample period than they do in the second half. This is indicative of systematic forces in the first sub-period that drive apart the repo rates of the two markets. Over time, they observed a trend that differences in the repo rates across the two markets become smaller on average but remain volatile from time to time.

Fan and Chu (2007) also identified two types of variables helpful in explaining the cross-market repo rate differences. The first type is measures of alternative investment opportunities. In the first sub-period, the exchange repo market was heavily used by investors in the IPO market due to institutional arrangements. New issue subscriptions and central bank interest rates explain much of the rate differences across the two repo markets. The other type of variable is the volatility difference in the short-term repo rates across the two markets. Volatility is important because it is a component of the

risk premium in the interest rates. In combination, these variables explain more than 40% of the variation in the rate discrepancies across the two repo markets.

2.2.2.3 Foreign exchange rates in China

From 1988 to 1994, China ran a complicated dual-track system of exchange rates in which the official exchange rate and a market-determined exchange rate coexisted. From 1994 to 2005.7, the Chinese currency, known as the Renminbi, was pegged to the US dollar. Under pressure from China's trading partners, the Renminbi has appreciated more than 20% against the US dollar since 2005.7. The global financial crisis in the fall of 2008 caused a sharp downturn in China's export growth, and the monetary authority of China re-pegged the Renminbi to the US dollar until 2010.3. While the nominal exchange rate between the Renminbi and the US dollar was invariant for most of the sample period in this study, the exchange rate between the Renminbi and the basket of currencies for China's trading partners varied, as those other currencies varied with the US dollar. In addition, because the inflation rates in China and in all of its trading partners fluctuated and the weight of trading volume with its partners changed over time, China's real effective exchange rate also fluctuated.

Huang and Guo (2007) investigated the extent to which the oil price shock and three other types of underlying macroeconomic shocks impact the trends in China's real exchange rate. By constructing a four dimensional structural VAR model, the results suggest that real oil price shocks lead to a minor appreciation of the long-term real exchange rate due to China's lesser dependence on imported oil than those trading partners included in the RMB basket peg regime and to rigorous government energy regulations. Real shocks, as opposed to nominal shocks, are found to be dominant in the variations of the real exchange rate.

Economic activities in China

China began its economic reforms in the early 1980s. Through its open-door policy, it

attracted a large amount of foreign direct investment, which propelled its high economic growth. The People's Bank of China became the central bank in 1984 and started to play an important role in fine-tuning economic activity. Between 1984 and 1994, the central bank's main objectives were to stimulate economic growth and to maintain stability in commodity prices. Balancing these two objectives, however, proved to be difficult. The real economy experienced dramatic, albeit turbulent, growth. Prior to 2009, the highest growth occurred in 1984, with a real GDP growth rate of 15.2%, and the lowest occurred in 1990, with just 3.8%. Overall, real GDP growth averaged around 10% per year. In 1995, after reaching the highest inflation rate seen since the economic reform, the central bank revised its policy goals and set inflation fighting as its priority. Various measures were adopted to cool off the economy, and they eventually proved effective. Both real economic growth rates and inflation rates fell considerably. The 1997 Asian Financial Crisis resulted in a serious decline in demand. The GDP growth rate dropped to below 8%, the inflation rate fell sharply, and interest rates followed suit.

Given the literature consulted above, the three hypotheses of this chapter are set out as follows. **Hypothesis 1:** Commodity prices in China tend to present overshooting behaviour in response to interest rate changes/monetary growth. **The null hypothesis:** Commodity prices in China tend not to present overshooting behaviour in response to interest rate changes/monetary growth. **Hypothesis 2:** Commodity prices in China tend to present overshooting behaviour in response to foreign exchange rate changes. However, this overshooting behaviour tends to be less significant than in the case of interest rate changes/monetary growth. **The null hypothesis:** Commodity prices in China tend not to present overshooting behaviour in response to foreign exchange rate changes. **Hypothesis 3:** A positive relationship exists between commodity prices in China and shocks from its economic activities. **The null hypothesis:** No positive relationship exists between commodity prices in China and shocks from its economic activities.

2.3 Data specification and methodology

2.3.1 Data specification

Due to the short history of the China's market economy and the government's heavy focus on developing the stock market, China's money market and interest rate liberalization are underdeveloped. However, the degree of marketization in China has been gradually improving. Until now, only the deposit rate and the lending rate have been officially controlled. The spot rate is basically driven by market-wide factors. China's spot interest rate is determined in two main markets: the inter-bank borrowing/offering market and the bond repurchase market.

To study the overshooting behaviour of commodities in response to interest rates, it is necessary that the interest rate should be market determined. This restraint rules out using the deposit rate or the lending rate, which are set by the central bank. In fact, the 1-year deposit changed only 19 times from 1997-10-23 until now (the lending rate changed a mere 21 times). Here, I follow Hong, Lin and Wang's (2009) idea of using the Chinese collateralized 7-day repo rates as the proxy for Chinese spot rates. Due to the segmentation of the OTC market (the inter-bank borrowing/offering market) and the bond repurchase market, I use the average of these two segmented collateralized 7-day repo rates as the interest rate variable, known as r_i . The proxy for monetary growth should be the annual growth rate of the narrow money supply and the broad money supply (M1 and M2, respectively), known as m_i .

From 2005.7.21, China ceased to peg the Yuan with the US dollar. The RMB started to float. Its value appreciated 21% until it re-pegged to the US dollar as one of the monetary measures taken to counter the shock of the global financial crisis. Under international pressure, especially from the US and EU governments, a second de-pegging of the RMB was initiated on 2010.6.21. Studying overshooting behaviour also requires that the foreign exchange rate be a market rate. Therefore, the effective range of the variable (the CNY/USD rate, known as fx_i) should start from 2005.7.21

One variable that can comprehensively describe economic activity is gross domestic product (GDP). (Dong, 2011) However, GDP data are released quarterly in China. In other words, 20 years (from 1990 to 2010) will only generate 80 GDP figures, and less available data might impact the significance of the empirical result. I adopt Akram's (2009) approach and choose added industry production growth (data released monthly) for the variable, known as y_i .

The commodities to be studied include industrial raw metals as well as agricultural commodities. Industrial raw metals include aluminium, copper and zinc, while agricultural commodities include cotton, wheat and soybeans. The commodity price is denoted with pc_i .

All of the data used are taken from the Wind system, a China-based financial database. The data used are stylized in month terms. The commodity futures prices (three metals: aluminium, copper and zinc; three agricultural products: bean, cotton and wheat) are indexed with their original value set as 100. The treatment of indexation could offer us a more standard and unified view of the price changes in futures prices. Interest rates and foreign exchange rates are in nominal terms. Monetary growth figures are generated from the year-on-year growth of narrow money supply and broad money supply, (M1 and , respectively). Economic activity figures are generated from the year-on-year growth of industry added value. The data basically range from 1998.1 to 2010.12. For aluminium and copper, data start from 1995.4; for cotton, they start from 2004.6; for zinc, they start from 2007.3; for the foreign exchange rate, the floating rate could be obtained from 2006.1 and the rest start from 1998.1.

From Table 2.1, I find that the futures prices of beans, copper and cotton have higher means, medians and standard deviations. In contrast, the futures prices of aluminium, wheat and zinc have smaller first and second derivatives. None of the commodity

futures price time series follow a normal distribution. Since the outbreak of the global financial crisis after the Lehman Brothers' bankruptcy, copper has experienced the most dramatic movement in prices: free fall followed by a rapid uptick – a V-shaped recovery. The beans futures price gained momentum prior to the crisis; it also plummeted in the crisis has not yet recovered its loss. Aluminium, cotton and zinc experienced minor losses. The notable exception is wheat, as its price went up during the crisis.

Insert figure 2.1 here

Insert Table 2.1 here

From Table 2.2, it can be found that the mean values of the repo rates in the two segmented markets are similar. The standard deviation of the exchange market repo rate is nearly 2 times of that of the inter-bank market repo rate. Looking closely at figure 2.2, I find a difference in the volatility pattern between the two types of repo rate. More impulse shocks occurred in the exchange market, while the volatility of the inter-bank repo rate was lower. The characteristics of the exchange market repo rates should be explained by the frequent presence of alternative investment opportunities such as equity IPOs and convertible bond IPOs. During the financial crisis period, I find that both rates were at historically low levels. The more stable inter-bank rate stayed at that low level for 8 months.

Insert figure 2.2 here

Insert Table 2.2 here

Table 2.2 also shows that the mean and standard deviation of the growth in M1 and M2 are of comparable scale. However, I could see that from the beginning of 2005, M1 behaved in a more dramatic manner despite their similar trends. M1 growth dropped much more deeply and climbed much higher than M2 growth during the global financial meltdown.

Table 2.2 and figure 2.2 very clearly show the movement of the Chinese Yuan (CNY): float, then re-peg during the global financial crisis, and then float again. Figure 2.2 shows a quite volatile pattern in the growth of industrial value added. It is interesting to observe its movement during the global financial crisis: It fell sharply a few months prior to the Lehman bankruptcy and then picked up a bit. When concern of a double dip appeared, it began to rebound robustly.

Table 2.3 presents the correlation between commodity futures prices and interest rates, monetary growth, foreign exchange rates and economic activities. Only wheat futures prices are negatively correlated with the two repo rates. Other commodity futures prices have positive correlations. The correlation between commodities and inter-bank repo rates is higher than that between commodities and exchange repo rates. All commodities have a positive correlation with M1 growth except for beans, while all commodities have a negative correlation with M2 growth except for wheat. All metals have positive correlations with the foreign exchange rate (metal prices increase with depreciation of the CNY), while all agricultural futures have negative correlations with the foreign exchange rate¹. All metals have strong positive correlations with the growth of industrial value added, while agricultural products have weak positive or negative correlations with the growth of industrial value added.

Insert Table 2.3 here

2.3.2 Methodology

2.3.2.1 SVAR model

Previous studies employing single equation models to investigate the relationship between commodity prices and financial and real economic variables have two drawbacks. One is simultaneity bias if the interest rate (or foreign exchange rate) is an endogenous variable. The other drawback is that single equation models cannot

¹ Prices for agricultural products increase with the appreciation of CNY

capture the dynamic interaction between commodity prices and financial and real economic variables over different time horizons.

The empirical analysis of chapter 2 is based on SVAR models. SVAR models, after an appropriate identification of shock structures, allow us to examine the response of commodity prices to unanticipated shocks, particularly to interest rates and the CNY/USD exchange rate, while taking into account the dynamic interaction between commodity prices and macroeconomic variables. The standard Choleski scheme is adopted to identify the shock structures.

The basic SVAR model is as follows:

$$z_t = A_1 z_{t-1} + A_2 z_{t-2} + \dots + A_p z_{t-p} + u_t \quad 2.1$$

Here A_i refers to a $k \times k$ matrix of adjusted structural coefficients, u follows the normal distribution of $N(0, \Sigma_u)$, and Σ_u is the variance–covariance matrix of the reduced form residuals consisting of $\frac{k(k+1)}{2}$ distinct elements. Four main macroeconomic variables are tested here, namely interest rate changes², foreign exchange rate changes, economic activity and commodity prices³. Hence, k should equal four.

In addition to the usual diagnostic checks, the Lagrange Multiplier (LM) test for autocorrelation should be conducted to ensure that the VAR is well specified. The Durbin-Watson (DW) test cannot be used with the VAR as it contains lagged dependent variables. If there is evidence of autocorrelation, more lags need to be added until the autocorrelation effect has been eliminated. The common methods for estimating the optimal lag length for a VAR are the Akaike information criterion, final prediction error, the Hannan–Quinn criterion and the Schwarz-Bayesian information

² To avoid increasing complexity, the monetary growth variable will not enter the equation simultaneously with the interest rate

³ I do not intend to include all of the commodity prices simultaneously in the model to limit the size of the model. The other commodity prices will be added and checked in turn.

criterion. The number of lags could then be decided based on these criteria.

Akram (2009) claimed that two lags of the variables (aside from the intercept) could adequately characterize the VAR models. Here, up to five lags of each of the variables is allowed. I check for various commodities and find that two lags of the variables for most of the commodities is sufficient, while three lags of the variables is necessary for the wheat SVAR equation.

Based on Akram's (2009) model, the variable ordering of z_t should be $\begin{bmatrix} y_i \\ r_i \\ fx_i \\ pc_i \end{bmatrix}$, which

is then set as the benchmark ordering. However, alternative orderings are also allowed, so that new conclusions could be reached.

To check whether the commodity price in China exhibits overshooting behaviour in response to interest rate/ monetary growth shocks and foreign exchange rate shocks as well as to explore the relationship between commodity prices and economic activities, I tend to use the impulse response function and the forecast error variance decompositions. The following sections address the basic mechanisms of how these work.

2.3.2.2 Impulse response function

The impulse response function is used to produce the time path of the dependent variables' response to shocks from all explanatory variables. If the equation system is stable, any shock should fade away. If the equation system is unstable, shocks would diverge, and an explosive time path could be observed

Consider a simplified VAR (1) model:

$$z_t = A_1 z_{t-1} + u_t \quad 2.2$$

where z is the variable vector $\begin{bmatrix} y_i \\ r_i \\ fx_i \\ pc_i \end{bmatrix}$; then the matrices and vectors in full should be

$$\begin{bmatrix} y_i \\ r_i \\ fx_i \\ pc_i \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} y_{i-1} \\ r_{i-1} \\ fx_{i-1} \\ pc_{i-1} \end{bmatrix} + \begin{bmatrix} u_{yi} \\ u_{ri} \\ u_{fxi} \\ u_{pci} \end{bmatrix}.$$

The next step is to calculate the value of each dependent variable given a unit temporal shock to variable y at time $t=0$. The value of each dependent variable can be determined at $t=0, 1, 2, 3$, etc. In this case, there is no effect in the r/m , fx and pc variable due to how the model is set. Specifically, the lower triangle matrix rules out the effect.

$$\text{Suppose } z_0 = \begin{bmatrix} u_{y_0} \\ u_{r_0} \\ u_{fx_0} \\ u_{pc_0} \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad z_1 = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} * \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \\ a_{41} \end{bmatrix}$$

$$z_2 = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} * \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \\ a_{41} \end{bmatrix} = \begin{bmatrix} a_{11}^2 \\ a_{21}a_{11} + a_{22}a_{21} \\ a_{31}a_{11} + a_{32}a_{21} + a_{33}a_{31} \\ a_{41}a_{11} + a_{42}a_{21} + a_{43}a_{31} + a_{44}a_{41} \end{bmatrix};$$

This process continues until the value of the dependent variable either becomes zero (stable) or very large (unstable). For variables r , m and fx , the procedure is the same.

The time paths in the form of figures are depicted. With the figure of the impulse response function, I could gain initial insight into whether a sudden shock from economic activity might result in dramatic real interest rate changes/ foreign exchange rate changes/ commodity prices changes; whether a sudden shock from interest rates or monetary growth might result in dramatic commodity price changes (the overshooting behaviour); whether a sudden shock from the foreign exchange rate might result in dramatic commodity price changes (overshooting behaviour).

Specifically, there are three curves in the impulse response function figures, one actual time path and two dashed lines marking the 95% confidence intervals. With the dashed lines, I could judge whether the overshooting is statistically significant at the 5% level in the short term.

2.3.2.3 Forecast error variance decomposition (FEVD)

Forecast Error Variance Decomposition is an alternative method for capturing the effects of shocks to the dependent variables. This technique determines the proportion of the forecast error variance of any variable in a system that is explained by innovations to each explanatory variable. It is usually the case that the series shock explains most of the error variance, although the shock will also affect other variables in the system. It is also important to consider the ordering of the variables when conducting these tests, as the error terms of the equations in the VAR are correlated. Therefore, the result is dependent on the order in which the equations are estimated in the model.

Take the likely figure of FEVD of pc as an example. Pc's FEVD should initially be attributed to itself. Over time, I might find that other variables, such as y, r, m and fx, also have explanatory ability for commodity price shocks. Conclusions could then be made accordingly.

2.4 Empirical results

2.4.1 Granger causality test

Before establishing the structural vector autoregressive (SVAR) model, a Granger causality test should be conducted to check whether the lagged variables could be incorporated into equations for other variables. Specifically, I need to know whether macroeconomic and monetary policy respond to changes in commodity prices or if commodity prices react to a shift in macroeconomic and monetary policy. Here, I set the lag to 2, identical to the lagged number in the SVAR equations.

Table 2.4 shows the Granger causality test result. I found that most of the null hypotheses could not be rejected. Interestingly, the hypotheses that all three metals do not Granger-cause industry activity are rejected. Intuitively, I could say that the quick response of metal prices should be seen as an expectation of future increased industrial activities. Meanwhile, it cannot be rejected that the 7-day inter-bank repo rate and M2 growth Granger-cause copper prices; that the 7-day exchange repo rate and M2 growth do not Granger-cause the zinc prices are rejected. Moreover, the null hypothesis that the foreign exchange rate does not Granger-cause the wheat price is rejected. Finally, I find that it might be probable that wheat and zinc prices Granger-cause the exchange interest rate and M1 growth; bean prices might Granger-cause M1 growth.

Insert Table 2.4 here

2.4.2 Impulse Response Function

In this section, I analyse the impulse responses based on the SVAR model. I present 2 standard deviations for the confidence intervals obtained from the structural shock as described in the model specification section.

As claimed in the model specification section, I first follow Akram's (2009) ordering of variables in the Structural Vector Autoregression. The SVAR equations are tested on the three types of interest rate (exchange repo rate, inter-bank repo rate and average rate) and two types of monetary growth rate (M1 and M2 growth rates). It should be noted that the impulse responses are quite uncertain in general, as the corresponding two structural standard deviation confidence intervals are relatively broad.

Before checking the commodity price response to macroeconomic variable shocks, I first observe how the macroeconomic variables interact with each other. Generally, I find that some of the impulse response could be quite well explained by economic

theory. Monetary growth (both M1 and M2 growth) presents better results than the interest rate; the inter-bank rate presents better statistical significance than the exchange rate while the exchange rate characteristics dominate the average rate in impulse response.

A sudden positive shock in the inter-bank 7-day repo rate results in slower appreciation of the foreign exchange rate and a moderate slowdown of industrial activities. Shocks from the exchange rate and the average rate have similar but much weaker effects. A shock from monetary growth leads to depreciation of the Chinese Yuan; it also boosts industrial activity for the next 5 months. It is worth mentioning that M1 growth has a stronger effect in prompting CNY depreciation and boosting industrial activity. I could say that monetary growth has played a significant role in boosting the economy.

A sudden shock to the Chinese Yuan, such as sharp depreciation, causes a minor increase in monetary growth (both M1 and M2) and a moderate increase in industrial activity. The impact of shock on the inter-bank repo rate is also significant. The consistency in these variables shows that monetary policy in China is likely to be launched in the form of packages so that economic growth could be forcefully boosted.

A sudden shock in economic activities (specifically industrial value added), for example, an overheating economy, might lead to dramatic tightening in monetary growth (both M1 and M2) and an instant increase in the inter-bank repo rate. The impacts of the exchange repo rate and the average rate are much weaker. Putting these together, I can see that the central banks have used both quantitative and qualitative monetary tools to cool down the economy when it is overheating.

2.4.2.1 Commodity price impulse responses

The results for the SVAR models depicted in figures 2.3 to 2.32 are generally consistent with theories suggesting a negative relationship between interest rates and commodity prices, a positive relationship between the monetary growth rate and commodity prices, and a positive relationship between economic activity and commodity prices. The results also confirm the hypothesis that some commodity prices, especially metals, overshoot after monetary growth shocks. However, the theories suggesting a negative relationship between the foreign exchange rate and commodity prices cannot be supported by the empirical evidence. I present the results for the SVAR models in detail in Figure 2.3-32. (5 monetary terms: R007_IB, R007_EX, RAVG, M1_GR, M2_GR; 6 commodity prices: aluminium, beans, copper, cotton, wheat, zinc)

Shocks in the interest rate should lead to overshooting commodity prices in response. However, evidence is quite scarce. I only find that a sudden shock in the exchange rate (the average rate) prompts overshooting behaviour in zinc futures prices. Meanwhile, positive “overshooting” between the interest rate and commodity prices, so-called “shock dependence,” has been observed between the inter-bank repo rate and aluminium (copper) prices and between the exchange repo rate (average rate) and bean prices. The prices peaked within 2 to 3 months after the interest rate shock and then subsided.

As I claimed in the introduction and model specification, the shock of monetary growth shows a better result than that of interest rate. All metals present overshooting behaviour to a sudden shock in the M1 growth rate; metals except aluminium also overshoot to shock in M2 growth rate. For agricultural products, beans overshoot in response to both M1 and M2 growth rate shocks. Generally, I find that commodity prices overshoot much more quickly in response to M2 growth shocks than to M1 growth shocks. It takes nearly 8 to 9 months to reach the peak for M1 shocks while

only 3 to 6 months for M2 shocks.

A sudden shock in a foreign exchange market prompts positive responses in some commodity prices. Specifically, I find that aluminium, beans and copper “reverse overshoot” to the foreign exchange shocks. Taking a look at the line graph for the foreign exchange rate again, I can find that the foreign exchange rate’s movement is unidirectional. Significant depreciation in the Chinese Yuan can rarely be observed during the sample period. Hence, it might be more appropriate to judge that the foreign exchange rate plays a minor role in commodity price movements.

Shocks in output could lead to a dramatic response in some commodity prices. In the case of the inter-bank repo rate and M1 growth, I find that aluminium, beans and copper overreact to industrial activity shock. In the case of M2 growth, aluminium, beans, copper and zinc present overreacting behaviour. In the case of the exchange repo rate and the average rate, all metals overreact to an output shock. For different combinations of macroeconomic variables, I find that bean prices respond the most quickly, almost instantly overreacting, while copper prices respond the most dramatically. The peak levels are generally the same across the three interest rate cases. The M2 growth rate scenario, however, shows a more significant result than the M1 growth rate.

Insert figure 2.3 to figure 2.32 here

2.4.3 Forecast Error Variance Decomposition

In this section, I investigate the contributions of different structural shocks to fluctuations in the modelled variables. Figures 2.33 to 2.37 show forecast error variance decompositions (FEVD) for different commodities over different forecasting horizons (in months) under different monetary terms. They display percentages for the variance of the error in forecasting a variable at a given horizon responding to four specific shocks. The shocks are denoted by the numbers 1, 2, 3 and 4: 1 for various

types of interest rate or monetary growth rate; 2 for the foreign exchange rate; 3 for industrial value added; and 4 for commodities.

I find that fluctuations in commodity prices are generally driven by shocks to commodity prices. From figures 2.33-2.35, it can be seen that the commodity price shock, presented with a black line, accounted for more than a 50% share in the long run for all commodities except aluminium and beans. For aluminium and beans, the foreign exchange rate tends to make a greater contribution in the long run.

From figures 2.36-2.37, a similar observation can be made. In the M1 scenario, the commodity price shock accounted for more than a 50% share of the shock in the long run for all commodities except aluminium. In the M2 scenario, the commodity price shock accounted for more than a 50% share in the long run for copper, cotton and zinc. For aluminium and beans, the foreign exchange rate tends to make a greater contribution in the long run. For wheat, the contributions made by the commodity and by the foreign exchange rate converge at 40% in the long run.

Shocks to foreign exchange rates account for some share of the shocks to certain commodity prices, while shocks to interest rates account for a negligible share of the shocks to all commodity prices (the only exception is zinc). Shocks to monetary growth (M1 growth, specifically) account for some share of the shock to all metal prices. Shocks to industrial value added account for some share of the shock to some metals.

In the inter-bank repo rate scenario, I detect that interest rate shocks account for an increasing share of price fluctuations for all of metals together with wheat. Specifically, interest rate shocks account for approximately 20% of fluctuations in aluminium and zinc prices in the long run. As for agricultural food prices, their fluctuation could be well explained by shocks to foreign exchange rates in the long run. In particular, the fluctuation of foreign exchange rates could account for more

than 40% of the bean price fluctuation. The intuition is that China's bean futures prices are closely connected to US bean prices. Any volatility in the USD/CNY rate will have a direct impact on the purchase cost of beans. The shock in economic activities accounts for approximately 30% for the fluctuation in aluminium and copper prices. The exception of zinc in this regard can be mainly attributed to its relatively short sample period.

In the exchange repo rate scenario (which is similar to the average repo rate scenario because the characteristics of the average rate are generally reflected by the more volatile exchange repo rate), the share that the repo rate could account for is negligible for all of the commodity futures prices. Similar to the inter-bank repo rate scenario, agricultural food price (aluminium prices as well) fluctuations could be well explained by the shocks to foreign exchange rates in the long run. The shocks to economic activity could account for approximately 30% of aluminium and copper price fluctuations.

In the M1 growth rate scenario, I find that the shocks in the M1 growth rate account for an increasing share of the price fluctuations for all of the metals. Foreign exchange rate shocks still account for a large share in the agricultural food price fluctuations. It is worth mentioning that the share that economic activity could account for is negligible for all of the commodity futures prices.

In the M2 growth rate scenario, I find that the share that the M2 growth rate could account for is negligible for all of the commodity futures prices in the long run. Foreign exchange rate shocks still account for a large share of the agricultural food price fluctuations in this scenario. I also find that shocks in economic activity account for an increasing share of price fluctuations for all of the metals except for zinc. Output shocks could contribute up to 20 percent of aluminium and copper shocks.

Combining all of the monetary scenarios, I find that the foreign exchange fluctuations

contribute to more than 20 percent of aluminium, beans and wheat fluctuations in all monetary scenarios. It is particularly notable that it accounts for nearly 20 percent of the volatility in cotton price fluctuations because the rest can only be attributed to the commodity price change itself.

Insert figure 2.33 to figure 2.37 here

2.5 Conclusion

In this chapter, I try to investigate the empirical relationship between commodity prices, real interest rates, the foreign exchange rate and economic activity in China's context. The analysis is based on structural vector autoregressive (SVAR) models. To incorporate the fact that China's spot interest rate market is segmented, my test is conducted with three different interest rate scenarios: the inter-bank repo rate, the exchange repo rate and the average repo rate. Moreover, to check whether quantitative monetary policy tools play a more effective role than price setting tools in China (Fan, Yu and Zhang, 2010), I add two monetary growth (M1 and M2 growth) variables.

My empirical evidence from the impulse response function support part of the theory between macroeconomic variables and commodity prices. A negative relationship between interest rates and commodity prices can be demonstrated for some metals. A positive relationship between monetary growth and commodity prices can be shown with statistical significance for several commodities. These results demonstrate that the monetary growth channel (mainly through the credit channel) plays a bigger role than the interest rate channel in promoting commodity prices in China. I also find that some commodity prices overreact to output shocks.

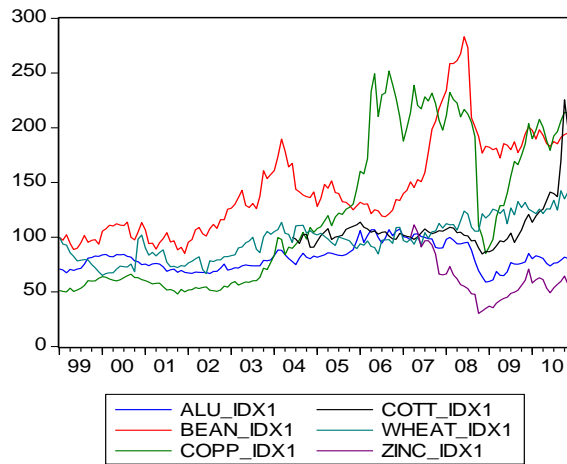
The forecast error variance decompositions (known as FEVD) suggest that the commodity price shock itself make the biggest contribution to the commodity price shock, generally. The fluctuation of the inter-bank interest rate could contribute an increasing share to the price volatility in all of the metals and wheat. The exchange

repo rate and average rate, however, have negligible explanatory power for commodity price shocks. Similarly, the M1 growth rate shock could help to explain an ever-increasing share of metal price fluctuation, while the M2 growth rate is negligible for explaining commodity price shocks. Foreign exchange rate shocks contribute to more than 20 percent of all commodity price shocks. Industrial output shocks comprise a 20 to 30 percent contribution to aluminium and copper.

The investigation of the overshooting behaviour of these commodities offers clear suggestions for investors. Indicators such as monetary growth and industrial value added growth could be added to their investment calendar. Prior to the announcement of these data, they could use their expectation for the data to decide what futures positions to take. Meanwhile, with the rapid pace of interest rate liberalization in China, changes in the interest rates of different markets should also be given increasing attention because it is likely that this price channel will have a greater and greater impact on commodity prices. For policy makers, the finding in this chapter is also crucial. Because the industrial economy is highly sensitive to changes in monetary policy, adjustment with quantitative rather than a qualitative tool could exert direct and powerful impact on the economy in the short term. However, the improvement of the interest rate pricing mechanism and the institutional framework should be prioritized if the government wants to let market factors play a bigger role.

Figures and Tables in Chapter 2

Figure 2.1: The line graph of commodity prices



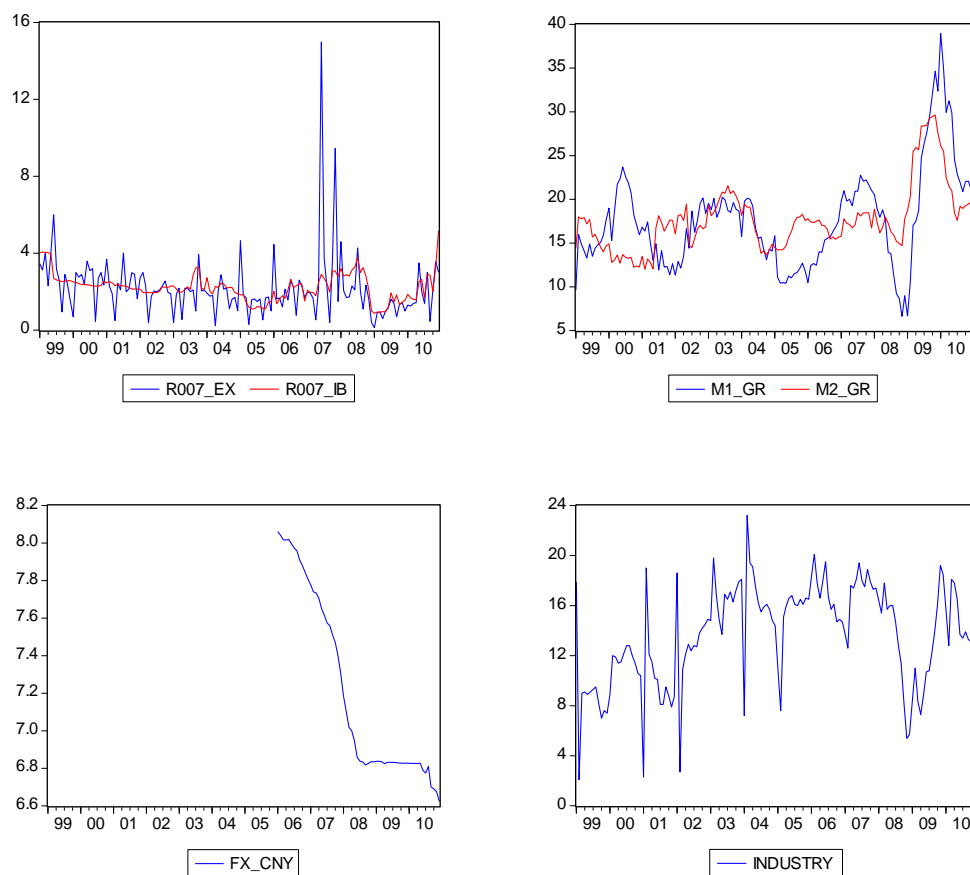
Note: ALU_IDX1 refers to the indexed value of the aluminium futures price; BEAN_IDX1 refers to the indexed value of the beans futures price; COPP_IDX1 refers to the indexed value of the copper futures price; COTT_IDX1 refers to the indexed value of the cotton futures price; WHEAT_IDX1 refers to the indexed value of the wheat futures price; ZINC_IDX1 refers to the indexed value of the zinc futures price

Table 2.1: Descriptive statistics for commodity prices

	COPP_IDX1	ALU_IDX1	ZINC_IDX1	WHEAT_IDX1	COTT_IDX1	BEAN_IDX1
Mean	122.41	81.35	61.24	98.04	109.47	145.42
Median	100.14	80.46	57.55	97.66	103.78	135.00
Maximum	251.73	107.49	111.26	142.38	225.55	283.10
Minimum	48.17	58.94	30.35	64.97	84.64	85.12
Std. Dev.	68.19	11.53	19.71	18.55	24.49	44.40
Skewness	0.47	0.53	0.84	0.24	3.16	0.89
Kurtosis	1.62	2.52	3.13	2.29	13.64	3.37
Jarque-Bera	16.68	8.17	5.39	4.44	503.95	20.03
Probability	0.00	0.02	0.07	0.11	0.00	0.00
Observations	144	144	46	144	79	144

Note: ALU_IDX1 refers to the indexed value of the aluminium futures price; BEAN_IDX1 refers to the indexed value of the bean futures price; COPP_IDX1 refers to the indexed value of the copper futures price; COTT_IDX1 refers to the indexed value of the cotton futures price; WHEAT_IDX1 refers to the indexed value of the wheat futures price; ZINC_IDX1 refers to the indexed value of the zinc futures price

Figure 2.2: Line graphs of interest rates, monetary growth, foreign exchange rate and economic activities



Note: R007_IB refers to the nominal 7-day inter-bank market repo rate; R007_EX refers to the nominal 7-day exchange market repo rate; RAVG refers to the average rate; M1_GR refers to the year-on-year growth of M1; M2_GR refers to the year-on-year growth of M2; FX_CNY refers to the nominal Chinese Yuan / US dollar exchange rate; INDUSTRY refers to the year-on-year growth of industrial value added

Table 2.2: Descriptive statistics for interest rates, monetary growth, foreign exchange rate and economic activities

	IB	EX	RAVG	M1_GR	M2_GR	FX_CNY	INDUST RY
Mean	2.25	2.19	2.22	17.57	17.66	7.21	13.70
Median	2.22	2.00	2.12	17.06	17.34	6.85	14.45
Maximum	5.17	14.98	8.94	38.96	29.64	8.06	23.20
Minimum	0.88	0.13	0.51	6.63	12.03	6.62	2.10
Std. Dev.	0.71	1.61	1.01	5.67	3.74	0.49	4.02
Skewness	0.76	4.23	2.66	1.05	1.36	0.55	-0.54
Kurtosis	4.85	31.52	16.89	4.74	5.12	1.62	2.87
Jarque-Be ra	34.24	5310.48	1327.61	44.43	71.44	7.80	7.18
Probabilit y	0.00	0.00	0.00	0.00	0.00	0.02	0.03
Observati ons	144	144	144	144	144	60	144

Note: IB refers to the nominal 7-day inter-bank market repo rate; EX refers to the nominal 7-day exchange market repo rate; RAVG refers to the average rate; M1_GR refers to the year-on-year growth of M1; M2_GR refers to the year-on-year growth of M2; FX_CNY refers to the nominal Chinese Yuan / US dollar exchange rate; INDUSTRY refers to the year-on-year growth of industrial value added

Table 2.3: Correlations between commodity prices and interest rates, monetary growth, foreign exchange rates and economic activity

	IB	EX	M1_GR	M2_GR	FX_CNY	INDUSTRY
ALU_IDX1	0.545	0.128	0.139	-0.394	0.700	0.801
BEAN_IDX1	0.460	-0.043	-0.143	-0.245	-0.235	0.166
COPP_IDX1	0.625	0.039	0.361	-0.262	0.425	0.830
COTT_IDX1	0.388	0.076	0.283	-0.023	-0.343	0.132
WHEAT_IDX1	-0.127	-0.128	0.279	0.454	-0.824	-0.310
ZINC_IDX1	0.243	0.28	0.267	-0.229	0.842	0.774

Note: ALU_IDX1 refers to the indexed value of the aluminium futures price; BEAN_IDX1 refers to the indexed value of the beans futures price; COPP_IDX1 refers to the indexed value of the copper futures price; COTT_IDX1 refers to the indexed value of the cotton futures price; WHEAT_IDX1 refers to the indexed value of the wheat futures price; ZINC_IDX1 refers to the indexed value of the zinc futures price; IB refers to the nominal 7-day inter-bank market repo rate; EX refers to the nominal 7-day exchange market repo rate; RAVG refers to the average rate; M1_GR refers to the year-on-year growth of M1; M2_GR refers to the year-on-year growth of M2; FX_CNY refers to the nominal Chinese Yuan / US dollar exchange rate; INDUSTRY refers to the year-on-year growth of industrial value added

Table 2.4: The Granger causality test between commodity futures prices and interest rates, monetary growth, foreign exchange rates and economic activity

X1	X2	Test 1	Test 2
ALU_IDX1	R007_IB	1.813 (0.167)	0.959 (0.386)
ALU_IDX1	R007_EX	1.887 (0.155)	0.618 (0.541)
ALU_IDX1	RAVG	1.561 (0.214)	0.189 (0.827)
ALU_IDX1	M1_GR	2.479 (0.08*)	2.009 (0.138)
ALU_IDX1	M2_GR	2.396 (0.09*)	0.668 (0.514)
ALU_IDX1	FX_CNY	0.920 (0.404)	5.938 (0.004****)
ALU_IDX1	INDUSTRY	5.336 (0.006****)	0.865 (0.423)
BEAN_IDX1	R007_IB	0.928 (0.400)	0.025 (0.975)
BEAN_IDX1	R007_EX	0.511 (0.600)	1.496 (0.228)
BEAN_IDX1	RAVG	0.249 (0.780)	1.024 (0.362)
BEAN_IDX1	M1_GR	2.860 (0.06*)	2.287 (0.105)
BEAN_IDX1	M2_GR	1.472 (0.233)	1.446 (0.239)
BEAN_IDX1	FX_CNY	4.876 (0.001****)	2.529 (0.089*)
BEAN_IDX1	INDUSTRY	1.096 (0.337)	0.293 (0.747)
COPP_IDX1	R007_IB	2.119 (0.124)	4.910 (0.009****)
COPP_IDX1	R007_EX	1.564 (0.213)	0.124 (0.884)
COPP_IDX1	RAVG	1.395 (0.251)	0.551(0.577)
COPP_IDX1	M1_GR	2.004 (0.139)	1.654 (0.195)
COPP_IDX1	M2_GR	0.254 (0.776)	2.950 (0.056*)
COPP_IDX1	FX_CNY	2.442 (0.091*)	1.890 (0.161)
COPP_IDX1	INDUSTRY	4.631 (0.01**)	0.343 (0.709)
COTT_IDX1	R007_IB	18.264 (0.000****)	1.842 (0.166)
COTT_IDX1	R007_EX	0.306 (0.737)	0.037 (0.964)
COTT_IDX1	RAVG	1.643 (0.200)	0.056 (0.946)
COTT_IDX1	M1_GR	0.812 (0.447)	0.741 (0.480)
COTT_IDX1	M2_GR	0.748 (0.477)	1.441 (0.243)
COTT_IDX1	FX_CNY	2.114 (0.130)	1.500 (0.232)
COTT_IDX1	INDUSTRY	0.127 (0.881)	0.524 (0.594)
WHEAT_INDX1	R007_IB	3.814 (0.024**)	0.312 (0.732)
WHEAT_INDX1	R007_EX	1.055 (0.350)	1.558 (0.214)
WHEAT_INDX1	RAVG	0.328 (0.721)	1.608 (0.204)
WHEAT_INDX1	M1_GR	0.365 (0.694)	1.184 (0.309)
WHEAT_INDX1	M2_GR	2.937 (0.056**)	0.761 (0.469)
WHEAT_INDX1	FX_CNY	1.516 (0.229)	2.634 (0.08*)
WHEAT_INDX1	INDUSTRY	0.143 (0.867)	0.984 (0.376)
ZINC_IDX1	R007_IB	1.738 (0.189)	0.281 (0.757)
ZINC_IDX1	R007_EX	12.950 (0.000****)	3.186 (0.05*)
ZINC_IDX1	RAVG	11.152 (0.000****)	1.577 (0.219)
ZINC_IDX1	M1_GR	3.376 (0.04**)	2.363 (0.108)
ZINC_IDX1	M2_GR	1.680 (0.199)	2.723 (0.08*)

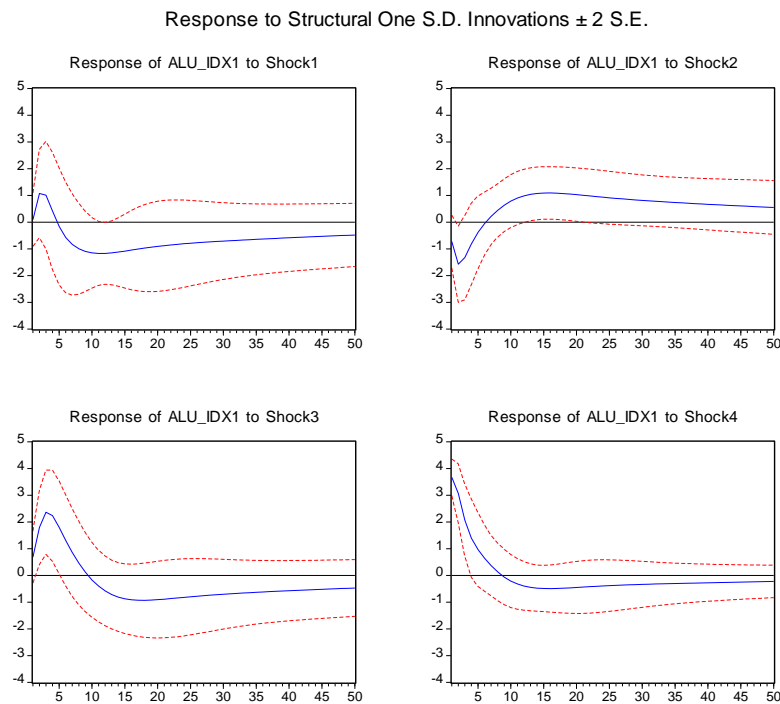
ZINC_IDX1	FX_CNY	0.321 (0,727)	0.138 (0.872)
ZINC_IDX1	INDUSTRY	5.701 (0.000***)	0.652 (0.526)

Note: Test 1: Granger non-causality from X1 to X2;

Test 2: Granger non-causality from X2 to X1;

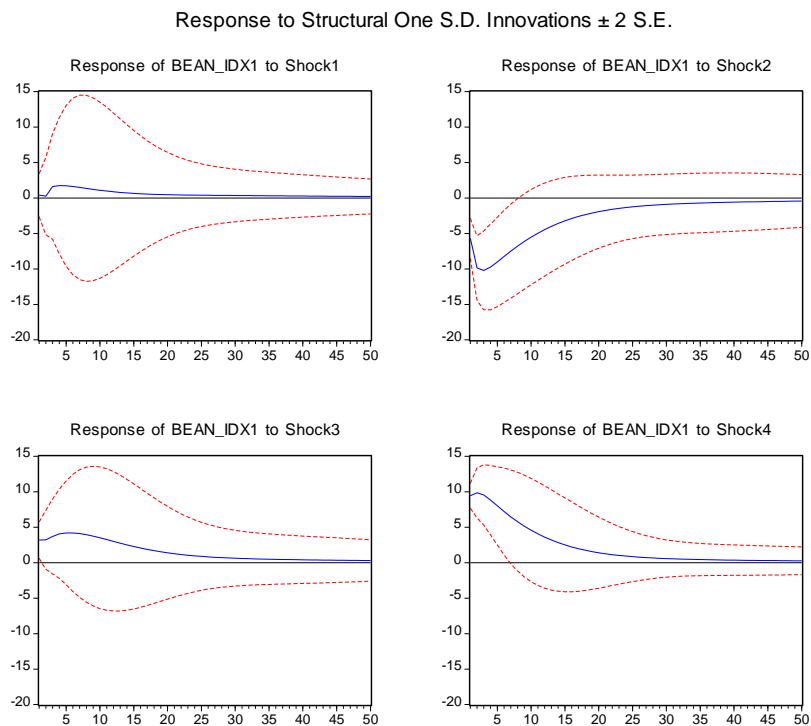
ALU_IDX1 refers to the indexed value of the aluminium futures price; BEAN_IDX1 refers to the indexed value of the beans futures price; COPP_IDX1 refers to the indexed value of the copper futures price; COTT_IDX1 refers to the indexed value of the cotton futures price; WHEAT_IDX1 refers to the indexed value of the wheat futures price; ZINC_IDX1 refers to the indexed value of the zinc futures price; R007_IB refers to the nominal 7-day inter-bank market repo rate; R007_EX refers to the nominal 7-day exchange market repo rate; RAVG refers to the average rate; M1_GR refers to the year-on-year growth of M1; M2_GR refers to the year-on-year growth of M2; FX_CNY refers to the nominal Chinese Yuan / US dollar exchange rate; INDUSTRY refers to the year-on-year growth of industrial value added

Figure 2.3: Impulse response functions of aluminium to shocks R007_IB, CNY, Industry and Aluminium



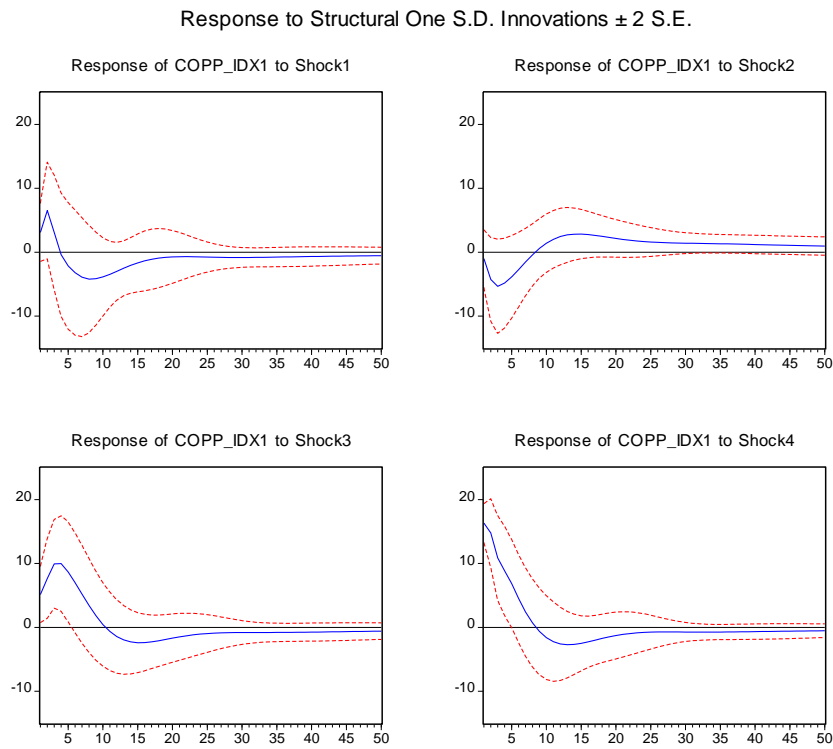
Note: shocks 1, 2, 3 and 4 refer to the shocks from aluminium, the 7-day inter-bank repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.4: Impulse response functions of beans to shocks R007_IB, CNY, Industry and Beans



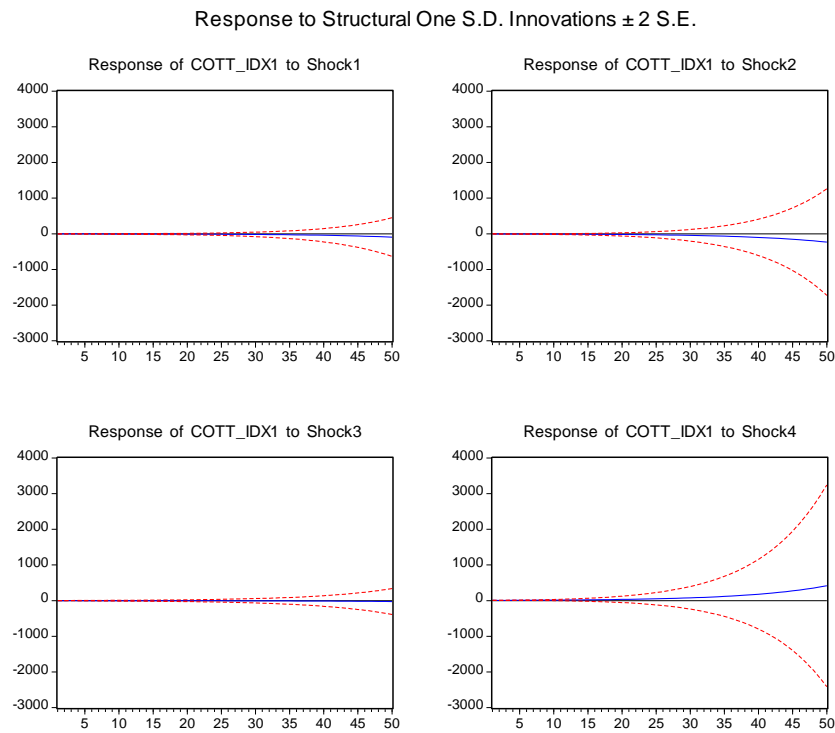
Note: shocks 1, 2, 3 and 4 refer to the shocks from beans, the 7-day inter-bank repo rate, CNY/USD rate and industrial value added, respectively

Figure 2.5: Impulse response functions of copper to shocks R007_IB, CNY, Industry and Copper



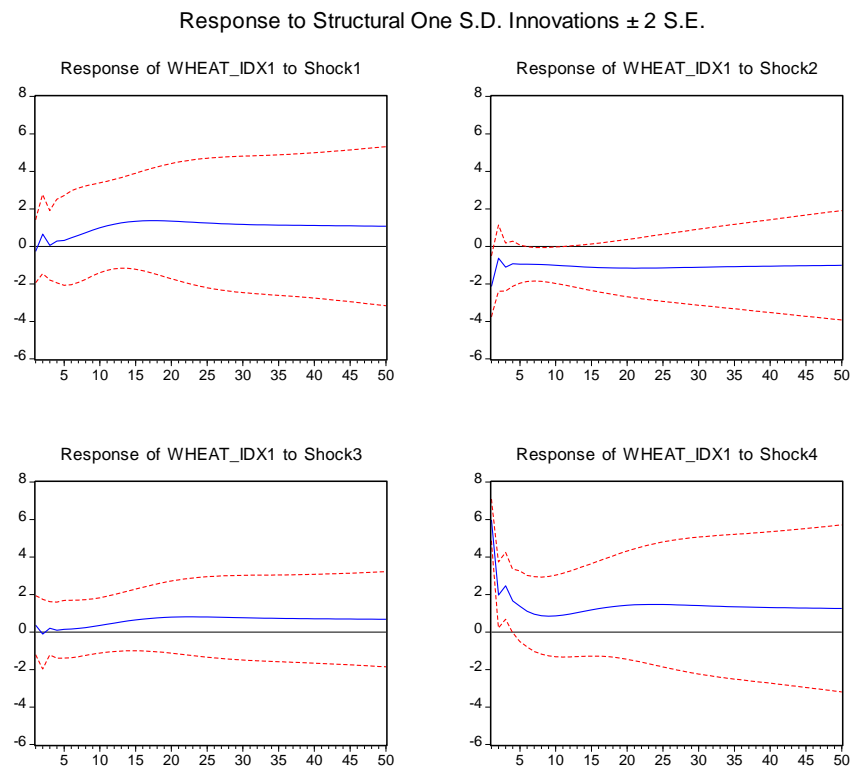
Note: shocks 1, 2, 3 and 4 refer to the shocks from copper, the 7-day inter-bank repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.6: Impulse response functions of cotton to shocks R007_IB, CNY, Industry and Cotton



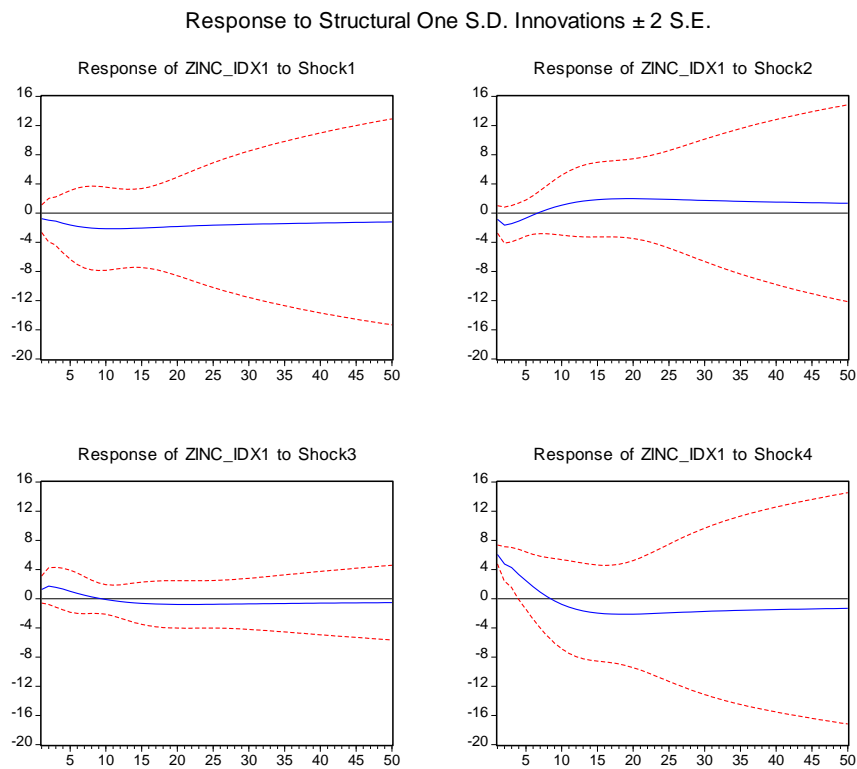
Note: shocks 1, 2, 3 and 4 refer to the shocks from cotton, the 7-day inter-bank repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.7: Impulse response functions of wheat to shocks R007_IB, CNY, Industry and Wheat



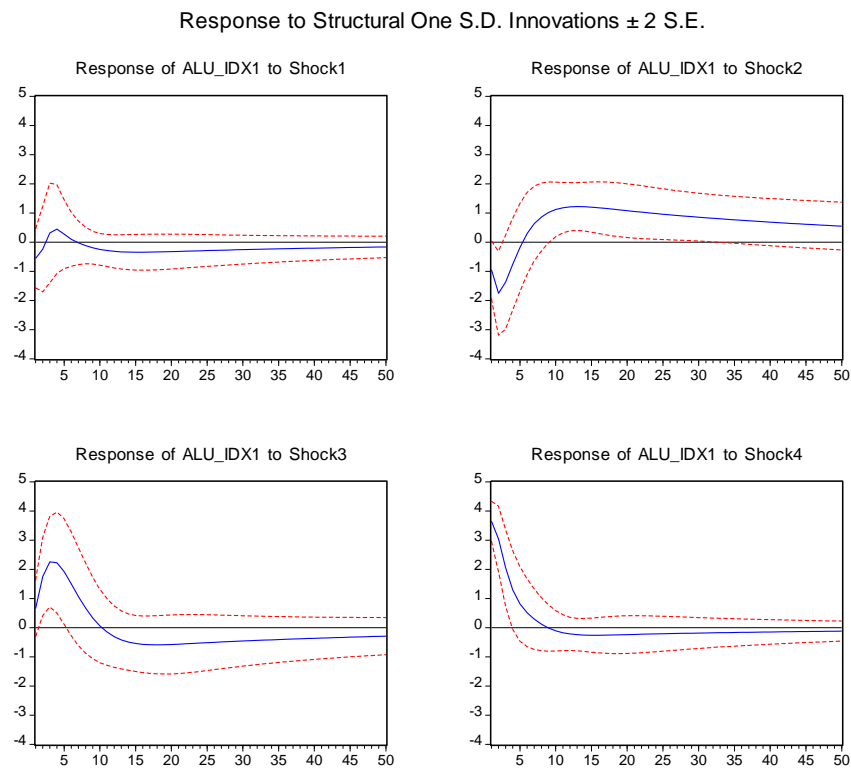
Note: shock 1, 2, 3 and 4 refer to the shocks from wheat, the 7-day inter-bank repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.8: Impulse response functions of zinc to shocks R007_IB, CNY, Industry and Zinc



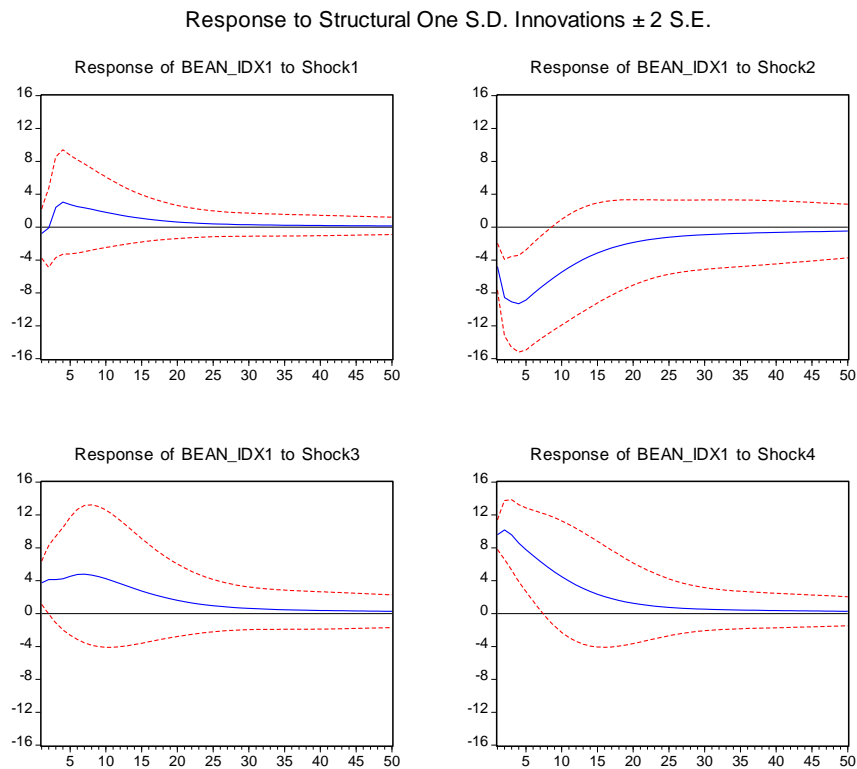
Note: shocks 1, 2, 3 and 4 refer to the shocks from zinc, the 7-day inter-bank repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.9: Impulse response functions of aluminium to shocks R007_EX, CNY, Industry and Aluminium



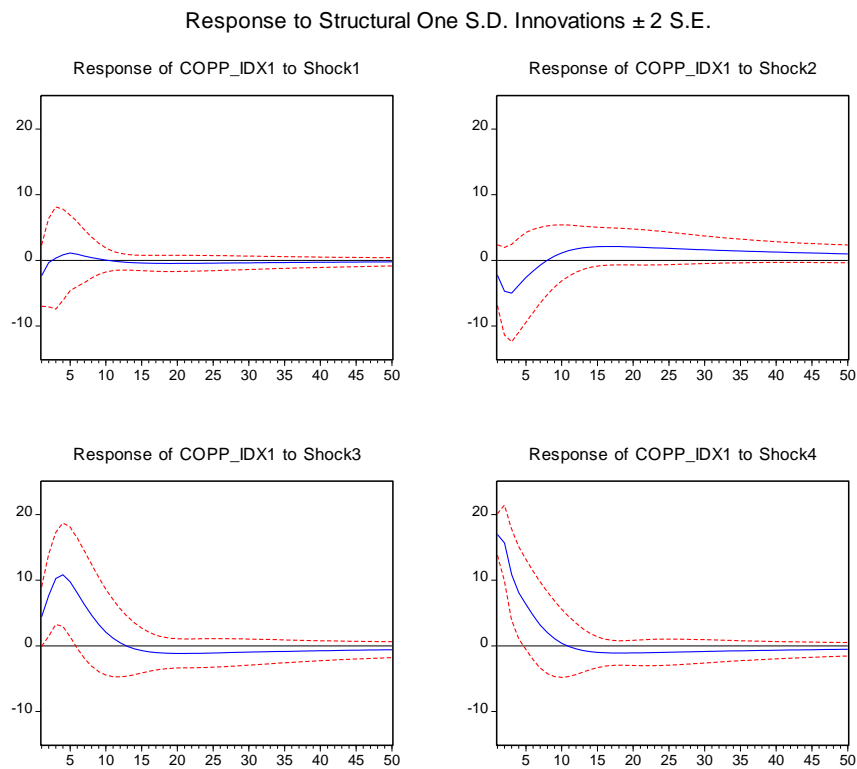
Note: shocks 1, 2, 3 and 4 refer to the shocks from aluminium, the 7-day exchange repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.10: Impulse response functions of beans to shocks R007_EX, CNY, Industry and Beans



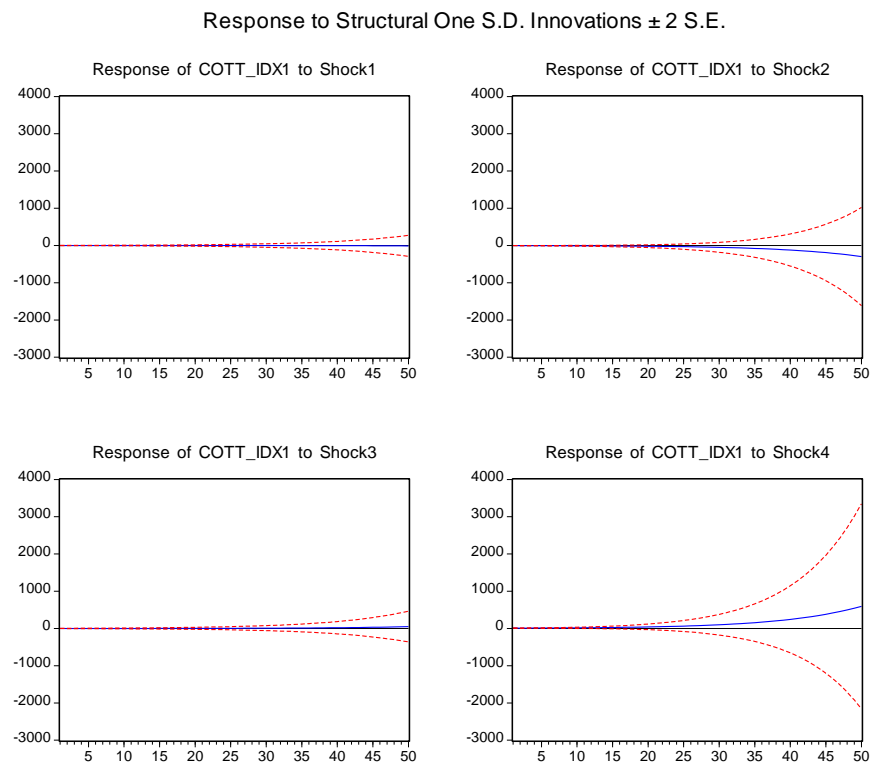
Note: shocks 1, 2, 3 and 4 refer to the shocks from beans, the 7-day exchange repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.11: Impulse response functions of copper to shocks R007_EX, CNY, Industry and Copper



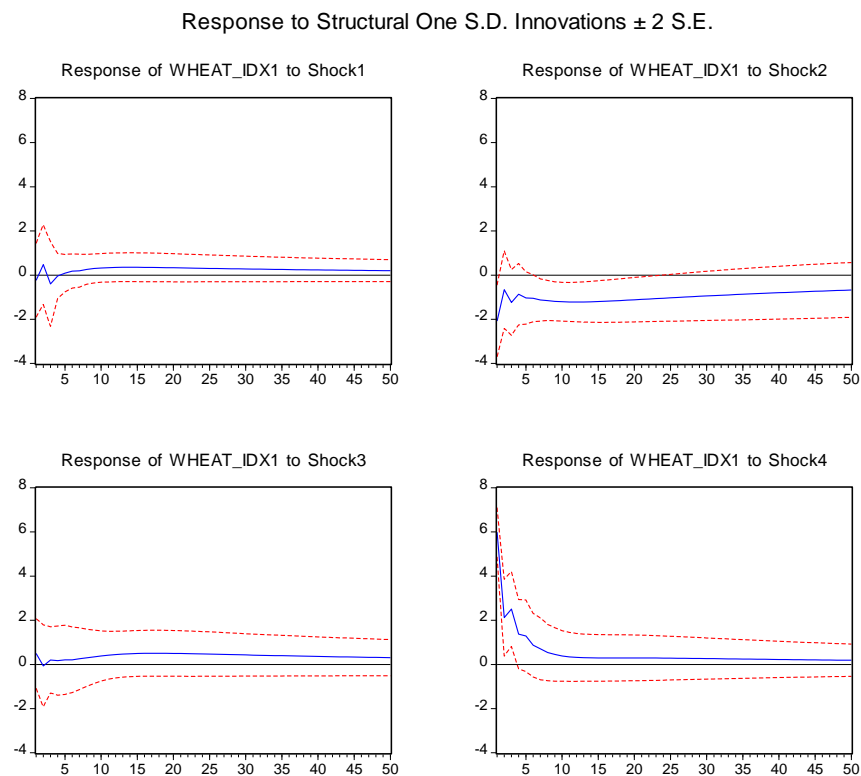
Note: shocks 1, 2, 3 and 4 refer to the shocks from copper, the 7-day exchange repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.12: Impulse response functions of cotton to shocks R007_EX, CNY, Industry and Cotton



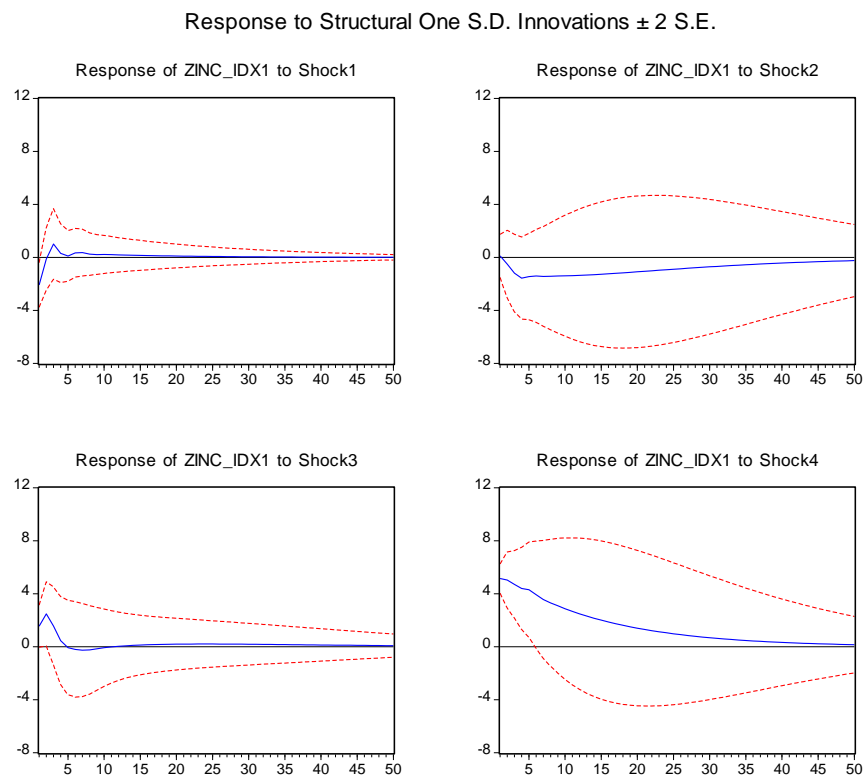
Note: shocks 1, 2, 3 and 4 refer to the shocks from cotton, the 7-day exchange repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.13: Impulse response functions of wheat to shocks R007_EX, CNY, Industry and Wheat



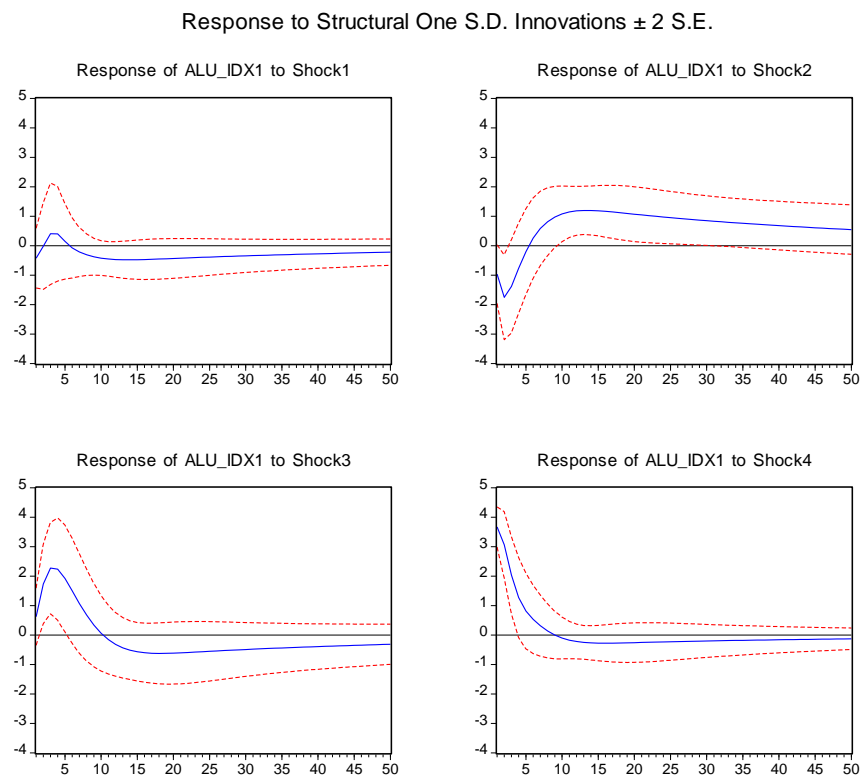
Note: shocks 1, 2, 3 and 4 refer to the shocks from wheat, the 7-day exchange repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.14: Impulse response functions of zinc to shocks R007_EX, CNY, Industry and Zinc



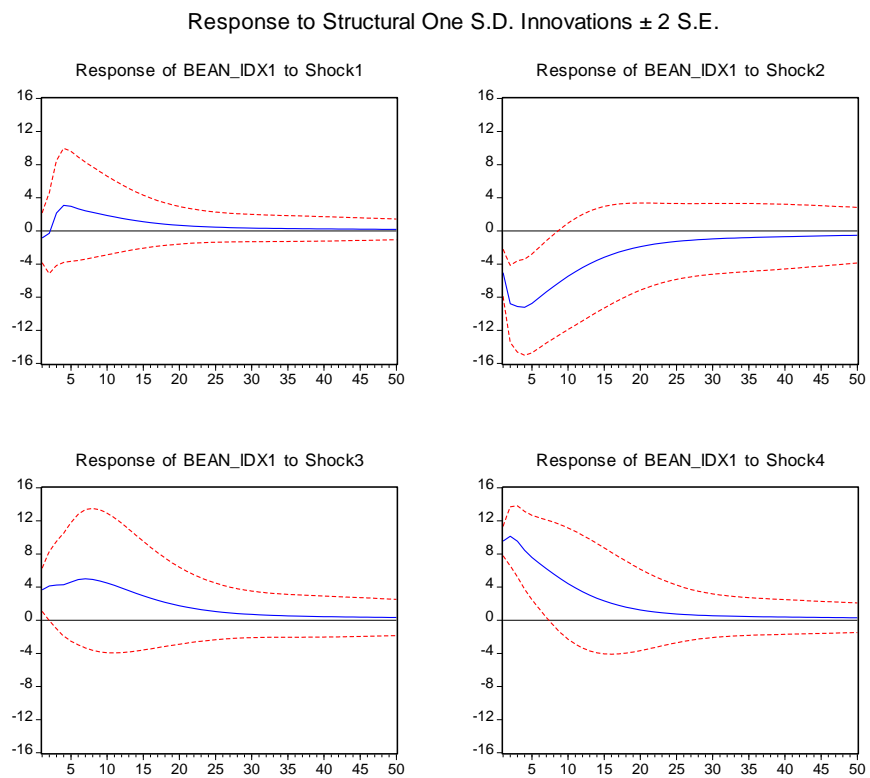
Note: shocks 1, 2, 3 and 4 refer to the shocks from zinc, the 7-day exchange repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.15: Impulse response functions of aluminium to shocks RAVG, CNY, Industry and Aluminium



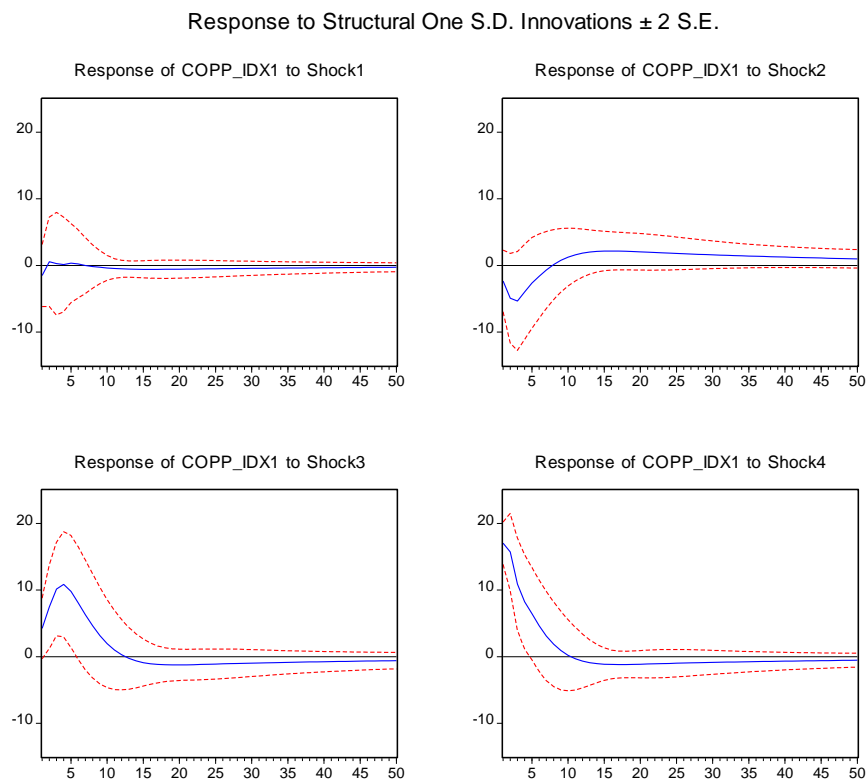
Note: shocks 1, 2, 3 and 4 refer to the shocks from aluminium, 7-day average repo rate, CNY/USD rate and industrial value added, respectively

Figure 2.16: Impulse response functions of beans to shocks RAVG, CNY, Industry and Beans



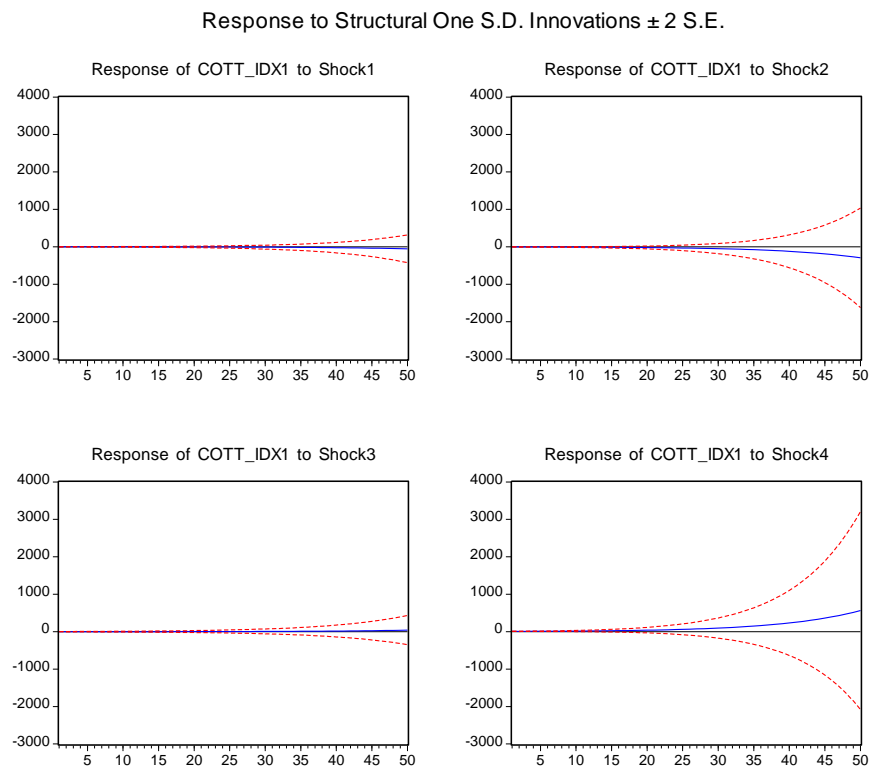
Note: shocks 1, 2, 3 and 4 refer to the shocks from beans, the 7-day average repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.17: Impulse response functions of copper to shocks RAVG, CNY, Industry and Copper



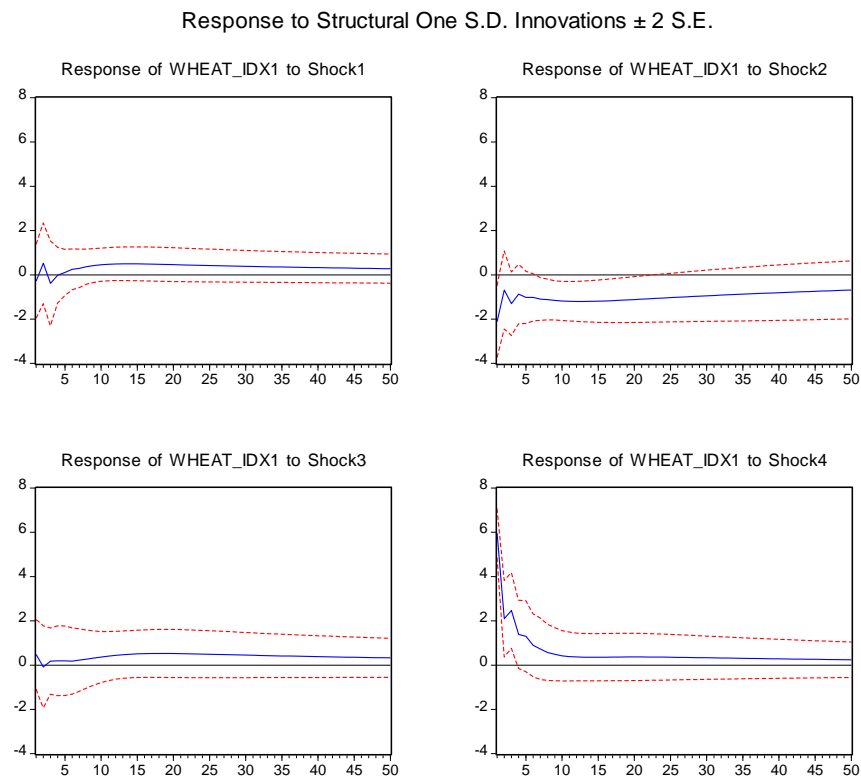
Note: shocks 1, 2, 3 and 4 refer to the shocks from copper, 7-day average repo rate, CNY/USD rate and industrial value added, respectively

Figure 2.18: Impulse response functions of cotton to shocks RAVG, CNY, Industry and Cotton



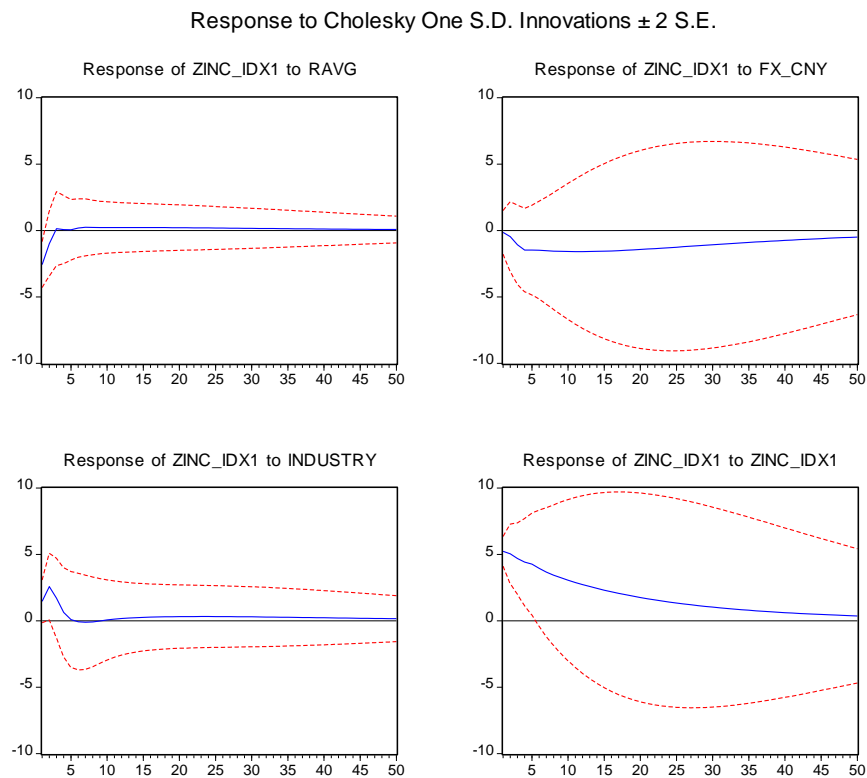
Note: shocks 1, 2, 3 and 4 refer to the shocks from cotton, the 7-day average repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.19: Impulse response functions of wheat to shocks RAVG, CNY, Industry and Wheat



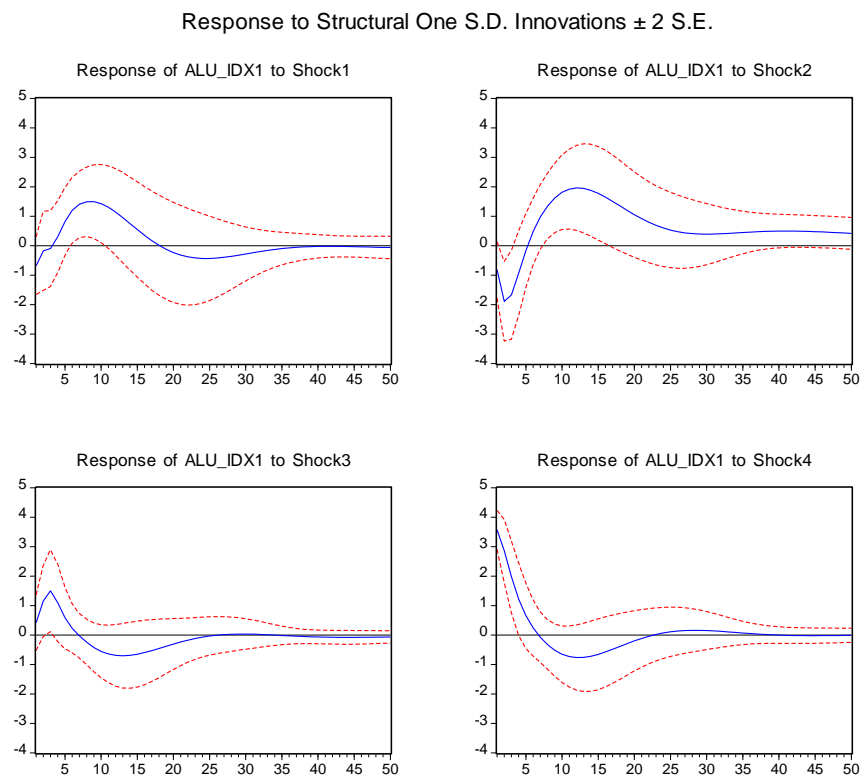
Note: shocks 1, 2, 3 and 4 refer to the shocks from wheat, the 7-day average repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.20: Impulse response functions of zinc to shocks RAVG, CNY, Industry and Zinc



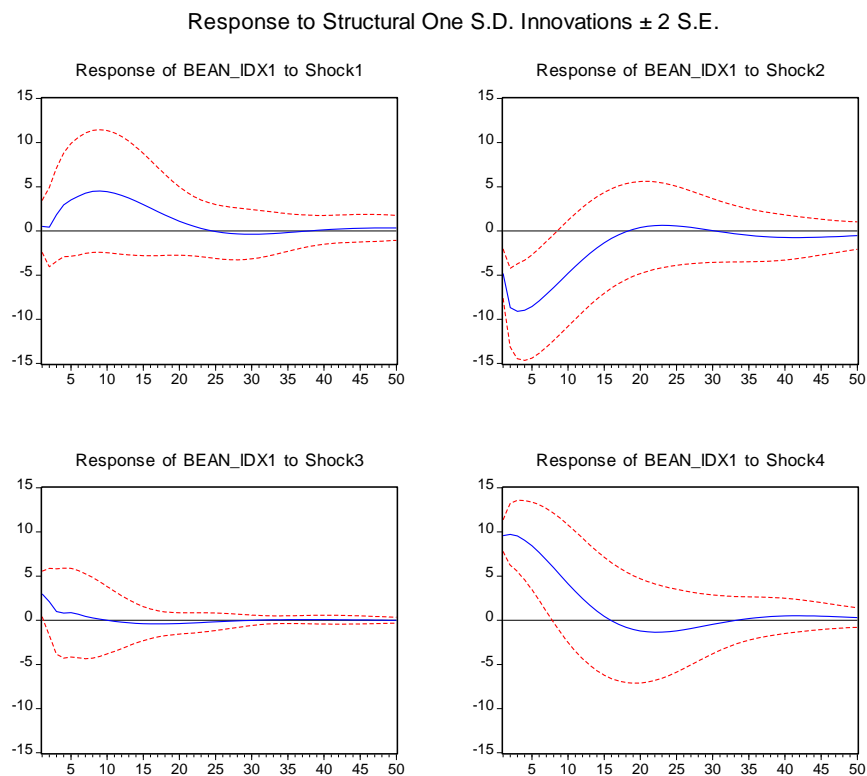
Note: shocks 1, 2, 3 and 4 refer to the shocks from zinc, the 7-day average repo rate, the CNY/USD rate and industrial value added, respectively

Figure 2.21: Impulse response functions of aluminium to shocks M1_GR, CNY, Industry and Aluminium



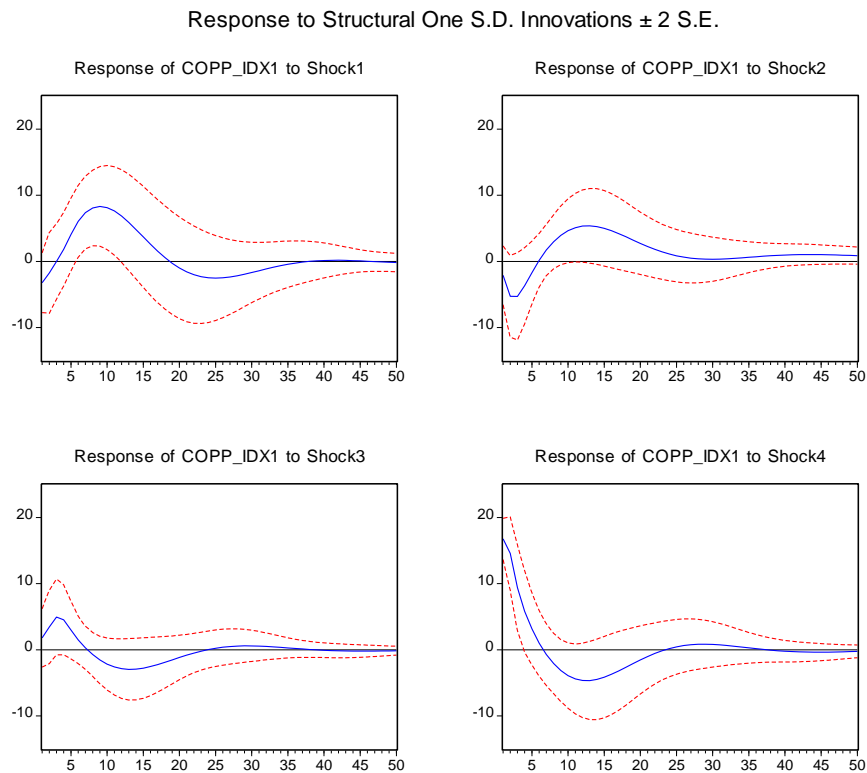
Note: shocks 1, 2, 3 and 4 refer to the shocks from aluminium, the M1 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.22: Impulse response functions of beans to shocks M1_GR, CNY, Industry and Beans



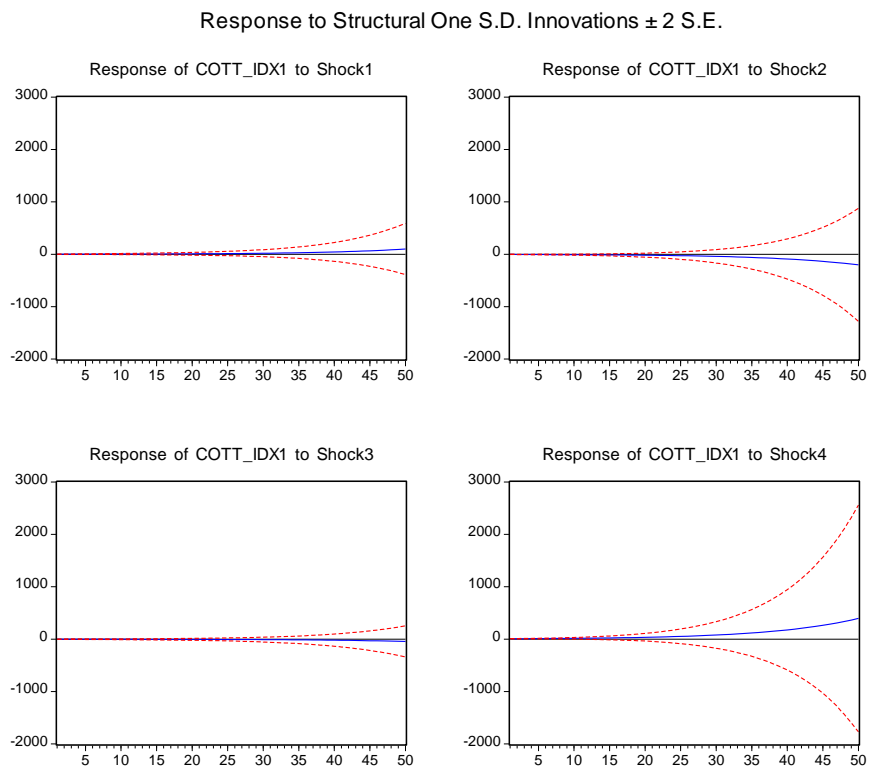
Note: shocks 1, 2, 3 and 4 refer to the shocks from beans, the M1 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.23: Impulse response functions of copper to shocks M1_GR, CNY, Industry and Copper



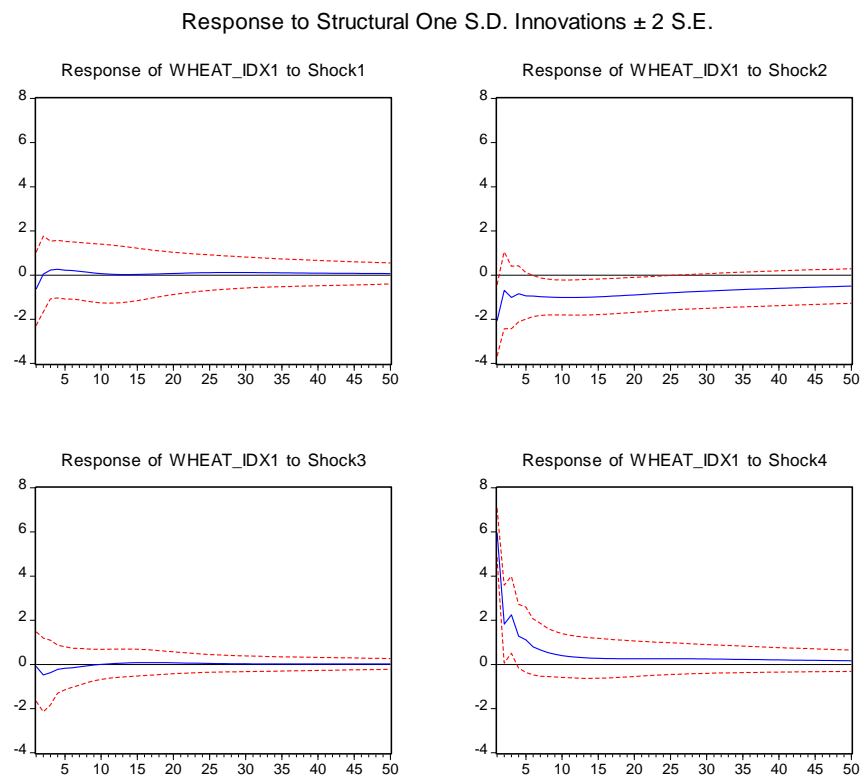
Note: shocks 1, 2, 3 and 4 refer to the shocks from copper, the M1 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.24: Impulse response functions of cotton to shocks M1_GR, CNY, Industry and Cotton



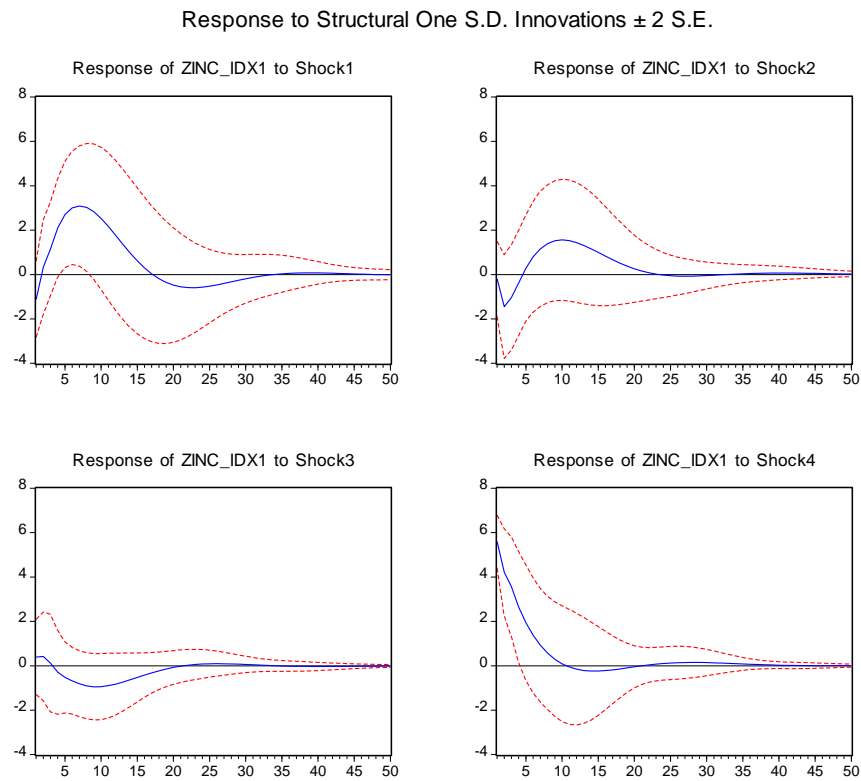
Note: shocks 1, 2, 3 and 4 refer to the shocks from cotton, the M1 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.25: Impulse response functions of wheat to shocks M1_GR, CNY, Industry and Wheat



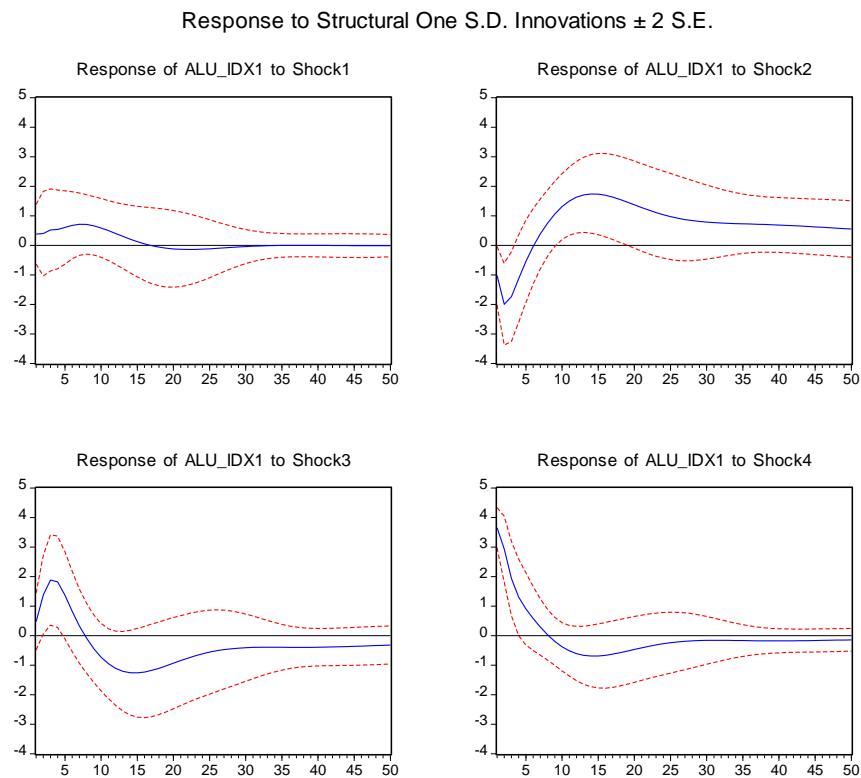
Note: shocks 1, 2, 3 and 4 refer to the shocks from wheat, M1 the growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.26: Impulse response functions of zinc to shocks M1_GR, CNY, Industry and Zinc



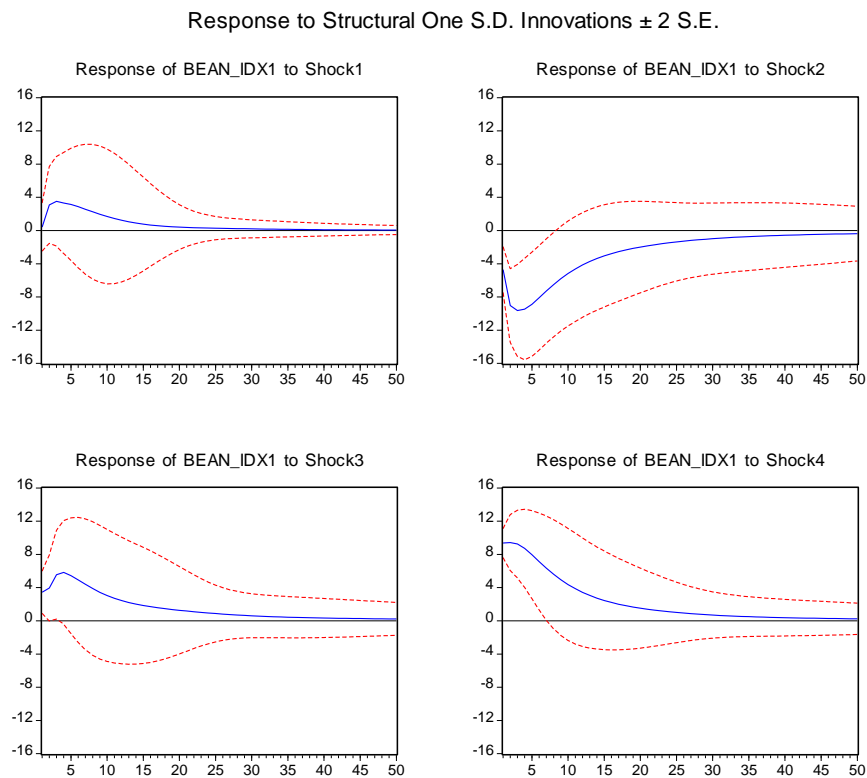
Note: shocks 1, 2, 3 and 4 refer to the shocks from zinc, the M1 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.27: Impulse response functions of aluminium to shocks M2_GR, CNY, Industry and Aluminium



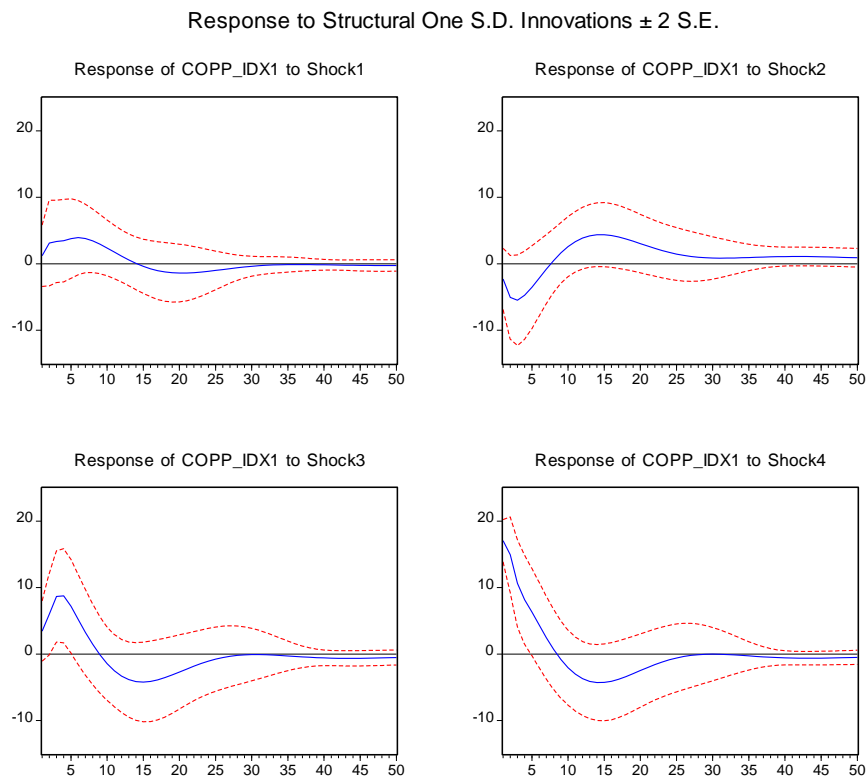
Note: shocks 1, 2, 3 and 4 refer to the shocks from aluminium, the M2 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.28: Impulse response functions of beans to shocks M2_GR, CNY, Industry and Beans



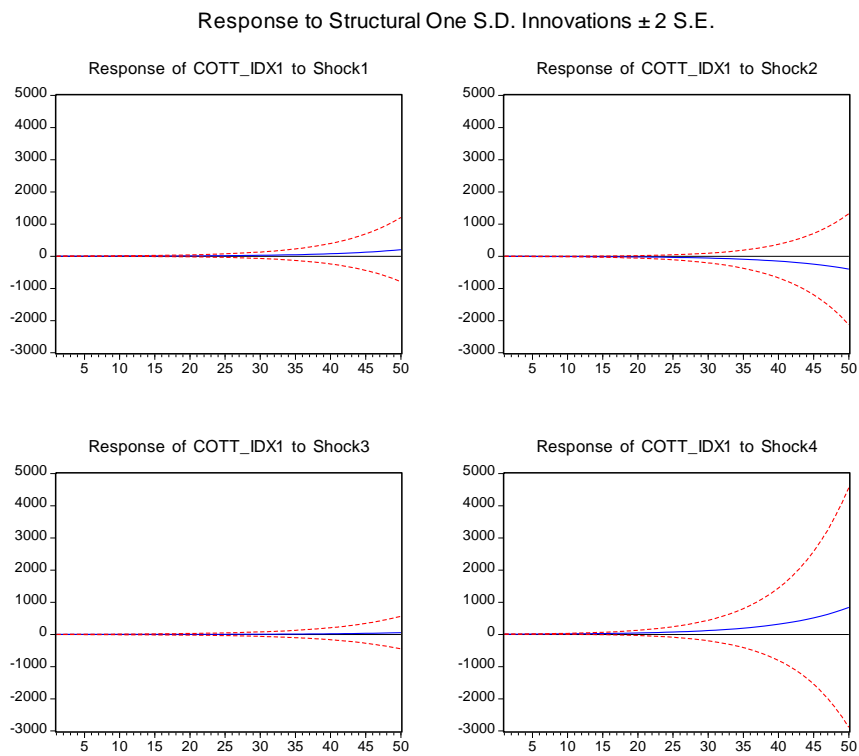
Note: shocks 1, 2, 3 and 4 refer to the shocks from beans, the M2 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.29: Impulse response functions of copper to shocks M2_GR, CNY, Industry and Copper



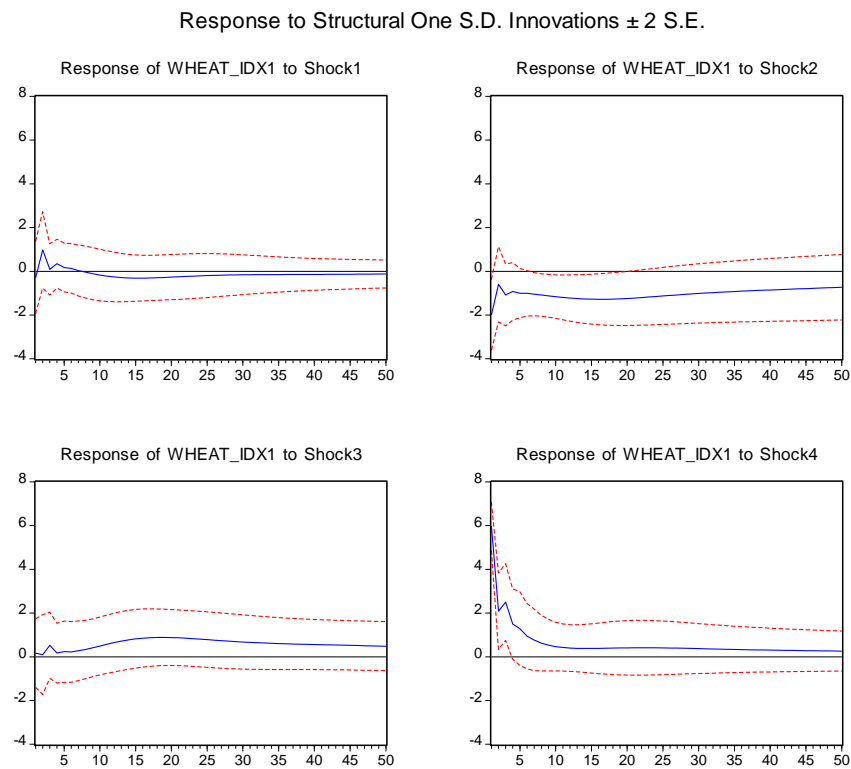
Note: shocks 1, 2, 3 and 4 refer to the shocks from copper, the M2 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.30: Impulse response functions of cotton to shocks M2_GR, CNY, Industry and Cotton



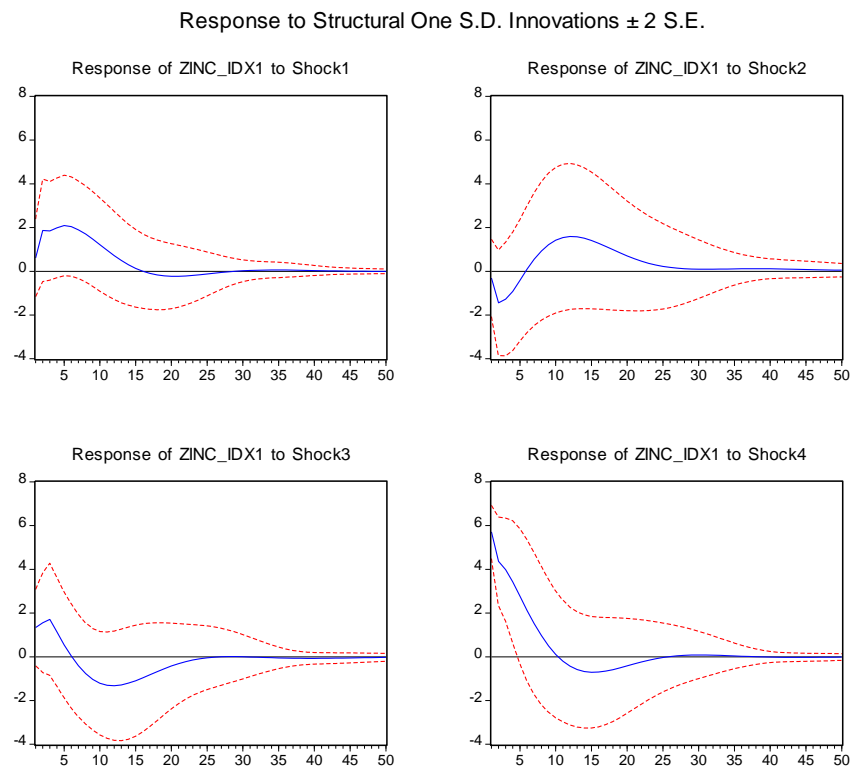
Note: shocks 1, 2, 3 and 4 refer to the shocks from cotton, the M2 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.31: Impulse response functions of wheat to shocks M2_GR, CNY, Industry and Wheat



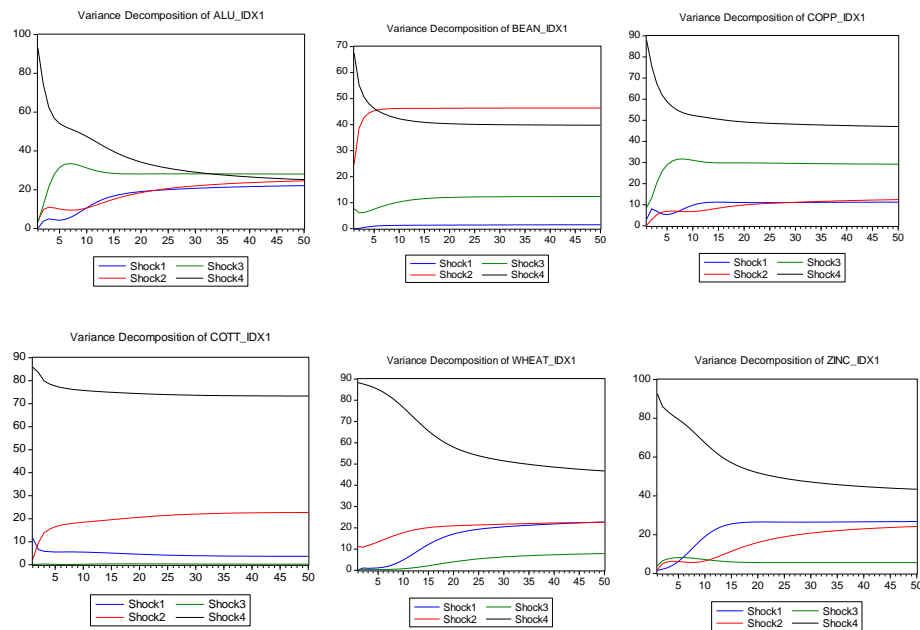
Note: shocks 1, 2, 3 and 4 refer to the shocks from wheat, the M2 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.32: Impulse response functions of zinc to shocks M2_GR, CNY, Industry and Zinc



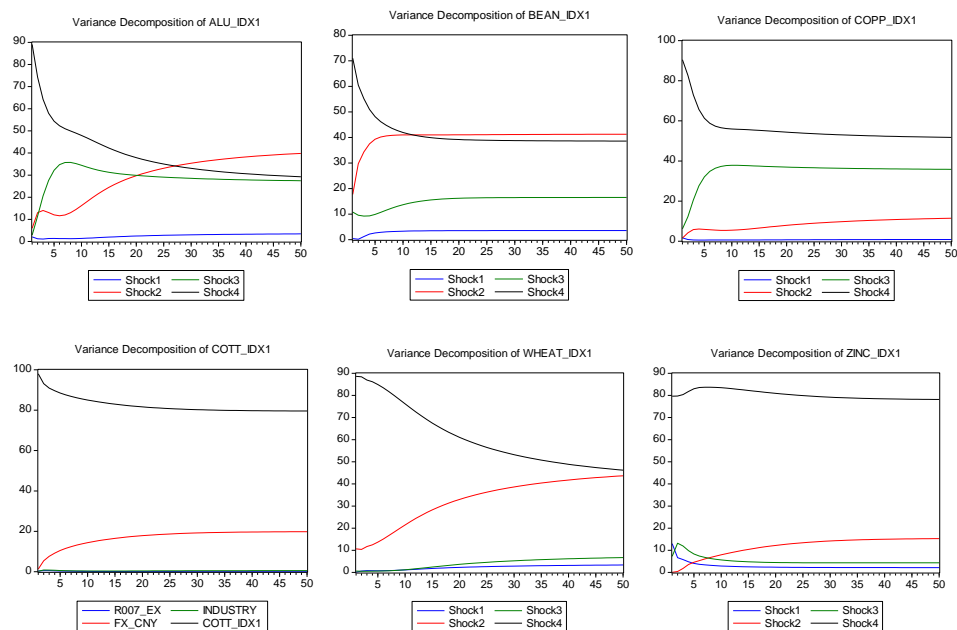
Note: shocks 1, 2, 3 and 4 refer to the shocks from zinc, the M2 growth rate, the CNY/USD rate and industrial value added, respectively

Figure 2.33: FEVD with shocks scenario: R007_IB, FX_CNY, Industry, and Commodity



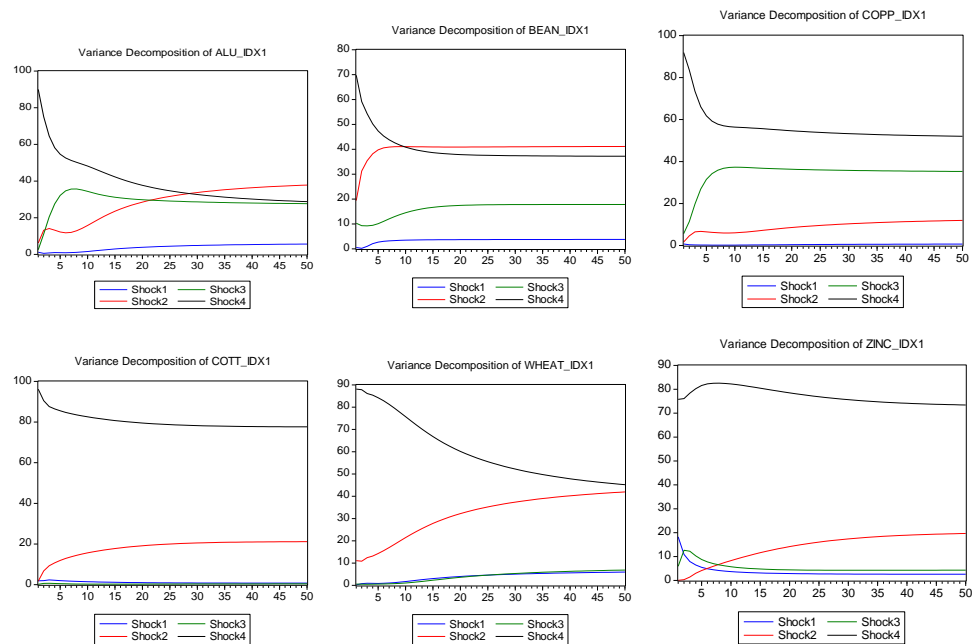
Note: shocks 1, 2, 3 and 4 refer to the shocks from the inter-bank repo rate, the CNY/USD rate, industrial value added and the commodities, respectively; from the top left to the bottom right, the six commodities shown are aluminium, beans, copper, cotton, wheat and zinc

Figure 2.34: FEVD with shocks scenario: R007_EX, FX_CNY, Industry, and Commodity



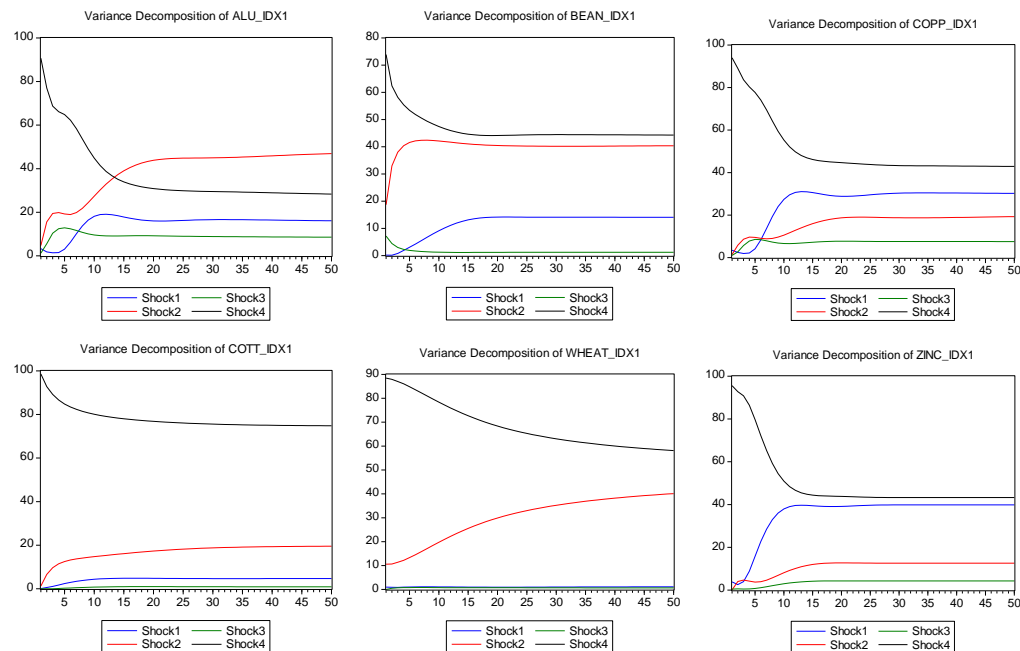
Note: shocks 1, 2, 3 and 4 refer to the shock from the exchange repo rate, the CNY/USD rate, industrial value added and the commodities, respectively; from the top left to the bottom right, the six commodities shown are aluminium, beans, copper, cotton, wheat and zinc

Figure 2.35: FEVD with shocks scenario: RAVG, FX_CNY, Industry, and Commodity



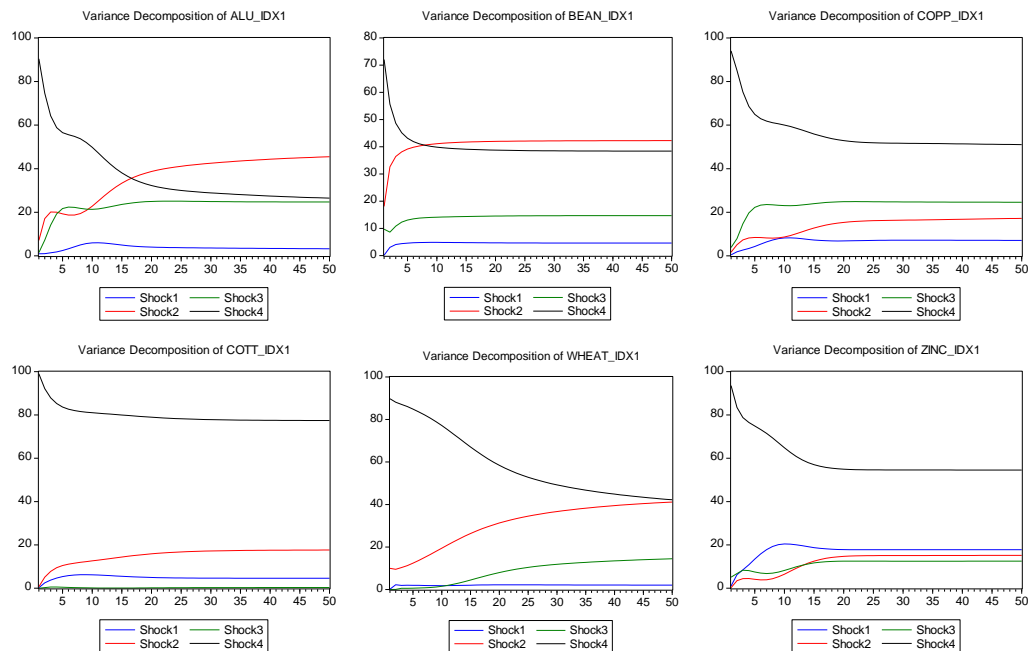
Note: shocks 1, 2, 3 and 4 here refer to the shock from the average repo rate, the CNY/USD rate, industrial value added and the commodities, respectively; from the top left to the bottom right, the six commodities shown are aluminium, beans, copper, cotton, wheat and zinc

Figure 2.36: FEVD with shocks scenario: M1_GR, FX_CNY, Industry, and Commodity



Note: shocks 1, 2, 3 and 4 refer to the shock from M1 growth, the CNY/USD rate, industrial value added and the commodities, respectively; from the top left to the bottom right, the six commodities are aluminium, beans, copper, cotton, wheat and zinc

Figure 2.37: FEVD with shocks scenario: M2_GR, FX_CNY, Industry, and Commodity



Note: shocks 1, 2, 3 and 4 refer to the shock from M2 growth, the CNY/USD rate, industrial value added and the commodities, respectively; from the top left to the bottom right, the six commodities shown are aluminium, bean, copper, cotton, wheat and zinc

Chapter 3 An empirical test on information spillover effects between the Chinese metal futures market and the global financial market

3.1 Introduction

Prior to the global financial crisis in 2008, China faced difficulties in the global commodity market: regardless of the commodity, when China bought it, its price would go up; when China sold it, its price would go down. This phenomenon indicated that China had practically no pricing power in the global commodity market. Generally speaking, pricing power is the ability to influence the price of goods in the market. Specifically, a country's pricing power in the global commodity market means that it can play an active role in promoting reasonable global commodity prices. With strong pricing power, the country's enterprises can gain a favourable position in the global commodity trade and achieve economic benefits. Clearly, pricing power is held by the dominant buyers and sellers. Spillovers occur from the dominant to the subordinate players.

In Chapter 3, I try to explore the impacts that China's futures market and the overseas futures market have on each other. Research from this angle could help reveal which side has stronger pricing power. Here, concepts should be clarified beforehand. Information spillover refers to the transmission of information across various financial markets. Under extreme market situations, information spillover could also be understood as "risk spillover" or "volatility spillover". Specifically, I aim at studying the information spillover effect between the domestic spot and futures markets as well as the information spillover effect and risk spillover effect between the domestic metal futures market and the overseas metal futures market. Moreover, to check whether China has gained pricing power in the global commodities market, I also study the risk spillover effect between the domestic metal futures market and other overseas financial markets.

From the literature consulted, the studied relationships between the futures market and the spot market focus mainly on price discovery, and few studies have been conducted on information spillover between the spot and futures markets or between the domestic futures market and the overseas futures market, especially the metal futures market in China. Hong and Cheng (2005) study information spillover between China's domestic stock market and the global equity market. However, vital differences exist between the stock market and the futures market. The broad adoption of leverage and margin call schemes, which are common practices in China's futures market, does not exist in stock markets. Therefore, it is necessary to make specific adjustments to study risk spillover in China's futures market.

Liu, Cheng, Wang, Hong and Li (2008) empirically studied information spillover effects between the Chinese copper futures market and the spot market. They take the upside risk into account (short-seller's risk) rather than merely focusing on the downside risk. They propose a more complicated research framework compared to those previously applied by scholars. However, this framework merely explores the information spillover between the domestic spot and futures markets; no attention is given to cross-border information spillover. Moreover, the dataset they use is out of date.

This chapter contributes to academia by filling an extant research gap. Scholars have rarely used the GARCH model specification and incorporated the Value-at-Risk model to test the information and risk spillover effect between the Chinese future market and the global financial market. This more sophisticated approach combined with a new data set enables us to explore cross-market interaction. More importantly, I can check whether China has recently gained power in international commodity pricing from the perspective of the information and risk spillover effects.

Practically, the empirical results could help practitioners gain a better understanding

of China's position in the global metal futures market, allowing them to take advantage of Chinese specific factors in their trading, hedging, and arbitrage strategies and global asset allocation.

To detect the cross-border spillover effect, I must ensure that the domestic futures market functions properly and effectively. In other word, the interaction between the domestic spot and futures markets should work in both directions, with the futures market playing the leading role. After checking the function of the domestic futures market, I will test whether the domestic futures market could impact the global futures market. Moreover, I try to find whether the risk spillover effect exists between the Chinese domestic futures market and other global financial markets (whether it has an extensive risk spillover effect).

The data used here range from 1995.4.17 to 2010.12.31, containing 3814 daily observations. The data for conducting the empirical test are taken from the Chinese financial database – Wind system. All of the data used are stylized in daily terms. Copper is studied for the spot futures interaction; Shanghai Futures Exchange (SHFE) and London Metal Exchange (LME) aluminium, copper and zinc futures are studied for cross-commodity market futures interactions; the Australian dollar- US dollar (AUDUSD) foreign exchange rate and the Australian stock index (ASX) are studied for cross-financial market interactions. The GARCH model specification and a Value-at-Risk model have been incorporated in the empirical research. In particular, both upside and downside value at risk have been taken into account for all of the financial time series that share the characteristics of allowing short selling. Then, a Granger causality test is conducted to see whether a causal link exists between the markets.

The empirical results clearly support some of my hypotheses. Specifically, the results indicate that in China's domestic market, futures pricing functions quite well because a two-way causal link is found to exist between spot and futures products, indicating

that the price discovery function performs effectively and reliably in China. As for the interaction between domestic and overseas futures markets, a causal link does exist from the SHFE to the LME; these results also hold for the extreme upside and downside scenarios. To some extent, this shows that movement in the SHFE could directly guide movement in the LME, indicating an increase in China's pricing power for commodities. As for the interaction between the SHFE metal market and overseas financial markets, no consistent conclusions are found, indicating that the Chinese factor may have limited impact on the global market as a whole.

The remainder of this chapter is organized as follows: section 3.2 introduces the literature consulted. Section 3.3 gives a description of the variables used, descriptive statistics of their data series and the methodology adopted. Then estimation and empirical results are presented in section 3.4. Finally, section 3.5 concludes the chapter.

3.2 Literature review

3.2.1 Literature

Garbade and Silber (1983) present a model for examining the price discovery role of futures prices and the effect of arbitrage on price changes in the spot and the futures commodity markets. Their empirical results suggest that the degree of market integration over the short term is a function of the elasticity of supply of arbitrage services. Grain commodities are well integrated over a month or two, while gold and silver markets are highly integrated even over one day. Moreover, their study on the role of the futures market in providing price information shows that the futures market generally dominates spot market because price change in the futures market lead price changes in the spot market.

Engle and Granger (1999) propose using cointegration analysis to study the equilibrium between imbalanced economic variables. This novel approach has been

widely used to explore the dynamic relationship between spot and futures prices. Haigh (1998) uses cointegration analysis to study the relationship between futures market and spot market prices. According to previous studies, for most futures products, a cointegrating relationship exists between the futures market and spot market prices. Hasbrouck (1995) defines price discovery in terms of the variance of innovations to the common factor, based on which the futures and spot markets' relative contributions to this variance can be examined. Tse (1999) investigates the minute-by-minute price discovery process and volatility spillovers between the Dow Jones Industrial Average (DJIA) index and the index futures. So and Tse (2004) use data from Hong Kong's Hang Seng Index, Hang Seng Index futures and the Tracker Fund to examine the price discovery function of the Hang Seng Index market via the Hasbrouck Gonzalo and Granger information sharing techniques and the Multivariate Generalized Autoregressive Conditional Heteroskedasticity (M-GARCH) model. Empirical evidence shows that the movements of the three markets are interrelated and that they have different degrees of information processing abilities.

In the Chinese futures markets literature, Hua and Zhong (2002) study price discovery in the Chinese futures market using the Garbade and Silber (1983) model. Hua (2005) study the relationship between spot and futures copper prices in China and propose an equation for copper futures pricing. Xu and Tang (2006) explore the interaction between volatility, trading volume and open interest in China's futures market. Tong (1997) and Ma (2005) investigate price discovery in the Mainland Chinese futures market. Hua and Zhong (2005) use cointegration analysis to study the relationship between the futures and the spot prices for copper and aluminium traded at the SHFE (Shanghai Futures Exchange). Gao (2004) studies the relationship between the soybean futures price and the spot price as well as the relationship between the SHFE copper price and the LME (London Metal Exchange) copper price. Pan and Zhang (2007) study the risk contagion between the Chinese oil market and overseas oil markets.

3.2.1.1 Information spillover effect and risk spillover effect

According to Wu, Wang and Xin (1997), no cointegration relationship existed between the Shanghai copper futures price and the London copper futures price prior to 1997. Moreover, it was not found that either market could dominate the other in terms of futures prices.

Kim (2005) investigated the nature of the information leadership of the US and Japan in the advanced Asia-Pacific stock markets. Instead of just relying on returns and return volatility spillovers from major markets, specific and disaggregated news events are also utilized with the aim of examining the nature of spillover effects from scheduled announcements covering US and Japanese macroeconomic variables in the advanced Asia-Pacific stock markets of Australia, Hong Kong and Singapore for the period 1991.1.2 to 1999.5.31. The investigation reveals that both US and Japanese announcement news exert significant first and second moment influences on the returns of the other markets, in general. Meanwhile, there is a complex array of significant market responses to various news announcements. There is also strong evidence that markets respond differently to bad news announcements compared to overall news (including both good and bad news) announcements, which indicates that the information content of each economic announcement is a source of tradable information rather than the act of releasing economic figures.

Zhou (2004) used the dataset ranging from 1997.9.21 to 2001.12.10, and found that the 3-month London copper price led the 5-month Shanghai copper price in lagged terms. However, the Shanghai copper futures price has not been found to lead the London futures price.

Hong and Cheng (2005) provided an empirical study on the spillover of extreme downside market risk among Shares A, B and H in the Chinese stock market and between the Chinese stock market and overseas equity markets. They find that strong

risk spillover exists between the Share A and Share B markets and that the occurrence of a high downside risk in Share B markets can help predict the occurrence of a similar risk in Share A markets. There also exists strong risk spillover between Share A and Share H markets and particularly between Share B and Share H markets. The latter have significant risk spillover with international stock markets. In contrast, although Share A markets have some risk spillover with the Korean and Singapore stock markets due to a closer economic relationship, they have no risk spillover with the equity markets in Japan, the U.S. and Germany.

Wu, Liu and Wu (2007) examine the volatility spillover effect of daily returns in the futures copper market between Shanghai and London by adopting a multivariate GARCH model. Their empirical result indicates that a volatility spillover effect existed between Shanghai and London during the entire period. Specifically, before 2001, the London copper futures market had a one directional spillover effect on the Shanghai copper futures market. However, after 2001, a bi-directional volatility spillover effect has been detected between the Shanghai copper futures market and the London copper futures market, thanks to the restructuring of the futures market in Shanghai. This shift marks increasing power for China in global commodity pricing.

Liu, Cheng, Wang, Hong and Li (2008) employ a parametric approach based on TGARCH and GARCH models to estimate the value at risk (VaR) of the copper futures market and spot market in China. Considering the short-selling mechanism in the futures market, the paper introduces two new notions: upside VaR and extreme upside risk spillover. The downside VaR and upside VaR are examined by adopting the above approach. Also, they use Kupiec's back-test mechanism to test the power of these novel approaches. In addition, they investigate information spillover effects between the futures market and the spot market by employing a linear Granger causality test, and Granger causality tests in mean, volatility and risk. Moreover, they also investigate the relationship between the futures market and the spot market using a test based on a kernel function. Empirical results indicate that significant two-way

spillovers exist between the futures market and the spot market, and the spillovers from the futures market to the spot market are much more striking than those in the other direction.

Lu, Li, Wang and Wang (2008) used Hong's method based on the Cross Covariance Function (CCF) and the Error Correction Model (ECM) to study Granger causality and information spillovers between major global crude oil markets including London, New York, and Dubai as well as Tapis and Minas in Southeast Asia. Using a methodology introduced by Hong, they find that the London and New York futures markets play dominant roles in information spillover, and WTI crude oil futures have a slight edge over Brent crude oil futures in information transmission. In addition, the empirical results indicate that Hong's method is more effective than ECM in testing Granger causality and information spillovers.

Kim and Nguyen (2008) provide comprehensive evidence of the spillover effects from US Fed and the European Central Bank (ECB) target interest rate news on the market returns and return volatilities of 12 stock markets in Asia- Pacific over the period 1999–2006. As a majority of the stock markets show significant negative returns in response to unexpected rate increases. The news spillover effects on the returns are generally consistent with the literature. While the results for the adjustment speed to the Fed's news are mixed across the markets, in general, ECB news was absorbed slowly. The return volatilities were higher in response to the interest rate news from both sources. Moreover, news from both central banks elicited tardy or persistent volatility responses. The findings have significant implications for all levels of market participants in the Asia - Pacific stock markets. (Kim and Nguyen, 2008)

Ding and Pu (2012) examine market linkage and information spillover across different financial markets: US stock, corporate bond, and credit derivatives markets in the pre-crisis, crisis, and recovery periods. Their results suggest that information

spills over across markets in a timely manner. They find that the market linkage became stronger in the crisis period. The findings could be explained by increasing volatility and deteriorating funding liquidity. In particular, volatility plays a dominant role in information transmission, which absorbs the liquidity effect when both volatility and liquidity are included as exogenous factors in a vector autoregressive model. (Ding and Pu, 2012)

Jiang, Konstantinidi and Skiadopoulos (2012) examine the effect of US and European news announcements on the spillover of volatility across US and European stock markets. They use synchronously observed international implied volatility indices at a daily frequency and find significant spillovers of implied volatility between US and European markets as well as within European markets. A stark contrast has been observed in the effect of scheduled versus unscheduled news releases. Scheduled (or unscheduled) news releases resolve (create) information uncertainty, leading to a decrease (increase) in implied volatility. Nevertheless, despite the fact that news announcements do affect their magnitude, they cannot fully explain the volatility spillovers. Their results are robust to extreme market events such as the recent financial crisis and provide evidence of volatility contagion across markets.

Sang, Cheong and Yoon (2013) provide empirical evidence of the relationship between spot and futures markets in Korea. In particular, the study focuses on the volatility spillover relationship between spot and futures markets using three high-frequency (10 min, 30 min, and 1 h time-scales) intraday data sets of KOSPI 200 spot and futures contracts. The results indicate a strong bi-directional causal relationship between futures and spot markets, suggesting that return volatility in the spot market can influence that in the futures market and vice versa. Thus, the results indicate that new information is simultaneously reflected in futures and spot markets. This bi-directional causal relationship provides market participants with important guidance on understanding the intraday information transmission between the two markets. Thus, on a given trading day, there may be sudden and sharp increases or

decreases in return volatility in the Korean stock market as a result of positive feedback and the synchronization of spot and futures markets.

3.2.2 Hypotheses

It can clearly be seen in the literature that the relationship between the futures market and the spot market focuses mainly on price discovery, and few studies have been conducted on information spillover between the spot and futures markets or between domestic futures markets and overseas futures markets, especially the metal futures market in China.

Hong and Cheng (2005) study information spillover between China's domestic stock market and the global equity market. However, vital differences exist between the stock market and the futures market in China. One of the most significant differences is that short selling in stock is forbidden in China, meaning that a long position in a stock always wins if the share price goes up. It is definitely not the same in the futures market. The heavy use of leverage and margin call schemes are common practice in the Chinese futures market. These characteristics imply that it is necessary to make special adjustments to study risk spillover in China's futures market.

Liu, Cheng, Wang, Hong and Li (2008) provide up-to-date work in my field of research. They empirically study information spillover effects between the Chinese copper futures market and the spot market. They take the upside risk into account, covering the short-seller's risk of loss. A more complicated research framework – using kernel-based Granger causality test - is proposed to substitute for the simplified linear Granger causality test applied in the previous literature. Nevertheless, this work merely explores the information spillover between the domestic spot and futures markets; no attention is given to cross-border information spillover. Moreover, the dataset in use covers until mid-2006. The inability to take data for more recent years' (especially the data range covering the global financial crisis) may make it difficult to reveal the increasing pricing power of China, especially after the 2008 global

financial crisis.

This paper aims at studying information spillover between the domestic spot and futures markets as well as between the domestic and overseas futures markets (including other overseas financial markets) using a new data set. This work will fill the extant research gap. More importantly, I will be able to determine whether China has recently gained power in international commodity pricing from the perspective of the information and risk spillover effects.

To detect the cross-border spillover effect, I must ensure that the domestic futures market functions properly and effectively. In other words, the interaction between the spot and futures markets must work in both directions, with the futures market playing the leading role. Thus, I have the first hypothesis: **Hypothesis 1:** A bi-directional causal link exists between the Chinese spot and futures metal markets, with the futures market playing the leading role; **Null hypothesis:** No bi-directional causal link exists between the Chinese spot and futures metal markets or a bi-directional causal link exists between the Chinese spot and futures metal markets, with the spot market playing the leading role.

After checking the function of the domestic futures market, I will test whether the domestic futures market could impact the global futures market. Thus, I have the following hypothesis. **Hypothesis 2:** a causal link exists between the Chinese futures metal market and the global futures metal market, with the direction being from China's market to the global futures metal market. **Null hypothesis:** No causal link exists between the Chinese futures metal market and the global futures metal market or a bi-directional causal link exists between the Chinese spot and global futures metal market, with the direction being from the global futures metal market to China's market.

Apart from the previous hypotheses, I am eager to know whether the risk spillover

effect exists between the Chinese domestic futures market and other global financial markets (whether it has extensive risk spillover effect). Thus, I have the following hypothesis. **Hypothesis 3:** A causal link exists between the Chinese futures metal market and the global financial market, with the direction being from China's market to the global financial market.

Null hypothesis: No causal link exists between the Chinese futures metal market and the global financial market or a bi-directional causal link exists between the Chinese futures metal market and the global financial market with the direction being from the global financial market to China's market.

3.3 Data and model specification

3.3.1 Data

The Chinese metal futures market has primarily three products: aluminium, copper and zinc. Because the majority of aluminium traders are hedgers, the volatility of aluminium futures price is comparatively mild. China has exceeded the United States as the largest copper consuming country in 2002, and China's copper consumption accounted for 21% of the world total consumption in 2004. The price fluctuations of copper, as an important industrial raw material, have a significant influence on Chinese and the world's economies. Just as Liu, Cheng, Wang, Hong and Li's (2008), copper futures is one of the most actively traded products in the Chinese futures market. Brought into the market in 2007, zinc futures also feature fierce price fluctuation.

To study the interaction between the Chinese spot and futures prices, I choose copper as the candidate variable. To qualify as a candidate requires the spot and futures market to be actively traded and prices to quickly reflect market changes. The first requirement rules out zinc as candidate because its spot market trading is inactive. The second requirement rules out aluminium because the volatility of its spot price is too low.

To study the interaction between the Chinese and overseas futures markets, I choose Shanghai Futures Exchange (SHFE) and London Metal Exchange (LME) aluminium, copper and zinc futures products as qualified candidates. To study the interaction between the Chinese futures market and overseas financial markets, I choose SHFE copper futures, the Australian dollar – US dollar exchange rate (AUDUSD), and the Australian stock exchange index (ASX) as the candidates. SHFE copper futures share the characteristics of high trading volume, varied market participants, and high flexibility to react to domestic and foreign market information. These characteristics (which aluminium and zinc products do not share) ensure that information is effectively channelled across different financial markets. It is known that Australia's economy is highly sensitive to changes in China's demand, especially in raw materials. A boom or bust in the infrastructure demand in China will be rapidly reflected in the AUDUSD rate and the ASX stock index. Here, I want to discover how such transmission works and whether it is channelled from the domestic copper price to the AUDUSD rate or via other paths.

Following Sarno and Valente (2005), all of the futures series in this chapter are conducted using the daily closing prices on futures contracts one month prior to the expiration month. The SHFE futures and spot prices are obtained from the Wind database (a Chinese financial database), while the LME futures prices are taken from the Reuters' system. The AUDUSD and ASX indexes are also taken from the Reuters' system using the data from the daily closing prices. I consider the period from 1995.4.17 to 2010.12.31, containing 3814 daily observations. All of the financial series are expressed in the natural logarithm form.

Insert Table 3.1 here

From Table 3.1, I can see that for the mean level for the rate of return is quite low for spot aluminium in absolute value compared with spot copper in China's market. In

both the Shanghai market and the London market, copper and zinc futures present a much higher rate of return than the aluminium futures product. These results indicate that aluminium trading is primarily conducted by hedgers, while speculative forces are prevalent in the copper and zinc futures markets.

Compared with the mean level of the rate of return for Chinese futures prices, the rate of return for spot prices is a little higher. It is worth mentioning that the mean level for the rate of return of metal futures is similar in the LME and the SHFE. The mean level of the rate of return for the AUDUSD is modest due to the huge trading volume in the foreign exchange market; the mean level of the rate of return for the ASX index is similar to those of SHFE and LME copper futures.

A brief observation from Table 3.1 is that the standard deviation of the aluminium spot and futures prices is among the lowest, only higher than that of the AUDUSD. The standard deviations of other time series are of comparable scale. Moreover, all of the time series have kurtosis significantly higher than 3, indicating a high peak and fat tails. Through the Jarque-Bera test, it can be confirmed that all of the times series follow non-normal distributions.

3.3.2 Methodology

3.3.2.1 Value-at-Risk (VaR) estimation

Value at risk (VaR) is known as a standard quantitative measure of potential economic loss for market risk. It can quantify the potential risk to determine its significance. According to Jorion (1996, 1997), VaR is defined as the maximum amount that can be lost within a specified time horizon and with a certain specified degree of confidence. Specifically, VaR is the maximum amount that can be lost with the probability of α , at the given confidence level of $1 - \alpha$ and given time horizon τ . Statistically, VaR is minus the α - quantile of the conditional distribution of the rate of return.

In the Chinese studies consulted, many focus on VaR estimation in the stock market;

very few studies have been conducted in the Chinese futures market. As the Chinese futures market gradually develops, it is showing a tendency toward increasing volatility. Therefore, it is of great importance to estimate VaR in China's futures market to quantify its risk and then to manage risks in the futures market effectively.

Liu, Cheng, Wang, Hong and Li (2008) introduce a parametric approach based on TGARCH and GARCH models to study the potential risks in China's futures and spot markets. Considering the short-selling mechanism, they separately study the risks associated with long positions and short positions. In particular, they introduce the notion of downside VaR to measure the risk of a long-side position and upside VaR to measure the risk of a short-side position. Specifically, they use the left α - quantile of the conditional distribution of the rate of return to measure the downside risk, and the economic implication for the spot market is the reduction in sales revenue caused by a significant price drop in the spot market; for the futures market, it is the risk of a price drop confronted by those buying futures contracts. The right α - quantile of the conditional distribution of the rate of return measures the upside risk; its economic implication is the increased loss caused by a significant price increase in the spot market, and the risk of price increases confronting those selling futures contracts in the futures market. The downside VaR and upside VaR at the $1 - \alpha$ confidence level could be defined respectively as follows:

$$P(Y_t < -V_t(\text{down}) | I_{t-1}) = \alpha \quad 3.1$$

$$P(Y_t > V_t(\text{up}) | I_{t-1}) = \alpha \quad 3.2$$

where Y_t refers to the rate of return, $V_t(\text{down})$ refers to the downside VaR, $V_t(\text{up})$ refers to the upside VaR, and I_{t-1} refers to the information set available at time $t-1$.

The core of the parametric VaR estimation is to estimate the volatility of a financial product. It is generally accepted that the higher the volatility is, the higher the risk. The conditional variance of a GARCH-type model could be used to measure the

volatility of an asset or an asset portfolio. J.P. Morgan (1996) brought forward RiskMetrics to measure risk. However, RiskMetrics cannot describe the leverage effect. Although a short-selling mechanism exists, the impacts of good news and bad news on the volatility of the futures market are asymmetric if the leverage effect is taken into consideration. Therefore, the asymmetric TGARCH model with normal innovations could be employed to estimate the conditional VaR of the futures market, and the GARCH model with normal innovations could be employed to estimate the conditional VaR of the spot market. Engle and Bollerslev. (1986), Bollerslev (1986, 1987), Engle, Lilien and Robins (1987), and Nelson (1991) use the GARCH model to estimate the conditional covariance as follows:

$$h_t = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} \quad 3.3$$

Zakoian (1994), Glosten, Jaganathan and Runkle (1993) introduced a TGARCH model to study the asymmetric impacts of good news and bad news on market volatility:

$$h_t = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} + \gamma \varepsilon_{t-1}^2 d_{t-1} \quad 3.4$$

where $d_t = 1$ when $\varepsilon_t < 0$, and otherwise $d_t = 0$. The threshold indicator (or signal variable) d_t describes the impact of information. When $d_t = 1$, it signals the impact of bad news; when $d_t = 0$, it signals the impact of good news. The parameter γ measures the difference between the impacts of good news and bad news on the financial market. A significant non-zero parameter indicates that the impacts of good news and bad news on volatility are asymmetric. When $\gamma > 0$, the impact of bad news on volatility is more significant; while when $\gamma < 0$, the impact of good news is more significant.

Employing a GARCH-type model, downside and upside VaR in the futures and spot markets could be calculated as follows:

$$V_{l,t}(\text{down } \alpha) = -\mu_{l,t} + z_{l,\alpha} \sqrt{h_{l,t}}, l=1, 2 \quad 3.5$$

$$V_{l,t}(\text{up } \alpha) = \mu_{l,t} + z_{l,1-\alpha} \sqrt{h_{l,t}}, l=1, 2 \quad 3.6$$

where $\mu_{l,t}$ is the conditional expectation of market 1, $z_{l,\alpha}$ is the left α - quantile of the distribution, which is followed by the standardized innovation of the GARCH-type model of market 1.

The estimation of VaR depends on the probability distribution and the given confidence level for the futures rate of return on financial products. Backtesting is used to test whether the given confidence level matches reality for the estimated VaR. If the loss exceeds the estimated VaR, the VaR model underestimates the real risk level; if the loss is below the estimated VaR, the VaR model overestimates the real risk level. Backtesting on the VaR model provides a way to check whether the VaR model adequately fits reality. Kupiec (1995) proposes a likelihood ratio test that treats the scenario when the rate of return exceeds the estimated VaR as an independent event with a binomial distribution. Suppose the confidence level is $1 - \alpha$, the sample size is T, the days of failure is N, then the sample failure frequency is $f = N/T$. The expectation for the failure rate should be α when the VaR model is correctly specified. Any significant difference between f and α indicates a misspecification of the VaR model. To check this hypothesis, Kupiec (1995) constructs a likelihood ratio test statistic:

$$LR = -2 \ln \left[1 - \alpha^{T-N} \alpha^N \right] + 2 \ln \left[1 - f^{T-N} f^N \right] \quad 3.7$$

Under the null hypothesis of the correct specification of the VaR model, it should be $LR \sim \chi^2_1$ asymptotically. The asymptotic critical values for the 10%, 5%, and 1% significance levels are 2.706, 3.841 and 6., respectively. If LR is larger than the critical value at a pre-specified level, then the null hypothesis is rejected, indicating that the VaR model is inadequate.

3.3.3.2 Granger causality test

The Granger causality test aims to explore the information spillover effects between the domestic and foreign futures markets as well as between the domestic spot and futures markets. In this chapter, I mainly conduct a linear Granger causality test to understand the information spillover in returns, volatility, extreme upside risk (for the short term) and extreme downside risk (for the long term).

Geweke, Meese and Dent, (1983) introduce test models for linear Granger causality.

Suppose that

$$Y_t = a_{10} + \sum_{i=1}^m a_{1i} Y_{t-i} + \varepsilon_{1t} \quad 3.8$$

$$Y_t = a_{20} + \sum_{i=1}^m a_{2i} Y_{t-i} + \sum_{j=1}^k \beta_j Y_{t-i} + \varepsilon_{2t} \quad 3.9$$

where $\{a_{1i}\}$ and $\{a_{2i}\}$ are the coefficients on the lagged values of Y_t , $\{\beta_j\}$ are the coefficients on the lagged values of X_t , ε_{1t} and ε_{2t} are normal white noise, and m and k are lag lengths. Given this specification, no Granger causality from X_t to Y_t is equivalent to the null hypothesis that

$$H_0: \beta_j = 0, j = 1, 2, \dots, k.$$

The associated F-test statistic is

$$F = \frac{ESS_1 - ESS_2 / k}{ESS_2 / N - k - m - 1} \quad 3.10$$

where ESS1 and ESS2 are the sums of the squared residuals in regressions 3.8 and 3.9; N is the size of sample Y_t .

Under the null hypothesis, the F statistic follows an F distribution with (K, N - k - m - 1) degrees of freedom. At significance level α , if $F > F_\alpha(K, N - k - m - 1)$, where $F > F_\alpha(K, N - k - m - 1)$ is the critical value at level α , the null hypothesis is rejected, and X_t Granger-causes Y_t .

3.4 Empirical Result

In this section, the empirical test is conducted in three steps: first, I choose the appropriate model to describe the volatility patterns of the time series; second, I compute the upside and downside risk by adopting the Value-at-Risk model. In this step, backtesting is conducted to check whether the VaR model could deliver satisfactory results – a low percentage of the sample cross the upside and downside VaR; finally, a Granger causality test is conducted to detect whether information spillover does exist across markets. Specifically, it is conducted considering three aspects: the information spillover and risk spillover effects between the Chinese domestic metal spot and futures markets; the information spillover and risk spillover effects between the Chinese and overseas metal futures markets; and the information spillover and risk spillover effects between the Chinese metal futures market and the overseas financial markets.

3.4.1 AR (m)-GARCH (p, q) test

3.4.1.1 Chinese spot metal market

From Figure 3.1, I can see that there are some irregular peaks in the spot metal market series. The eminent volatility clustering suggests that the daily volatility in the copper market is significant, abrupt, and displays conditional heteroskedasticity.

Table 3.2 reports the results of the augmented Dicky–Fuller test for stationarity for the series. The results indicate that the null hypothesis (there exists a unit root) is rejected under a 1% significance level. Therefore, the series is stationary.

Insert table 3.2 and table 3.6 here

I use the partial autocorrelation function and the autocorrelation function to determine the order of an AR process in the mean equation. Based on the characteristics of the residual series, I determine the order of ARCH and GARCH in the variance equation.

Specifically, I build the AR (1) – GARCH (1, 1) model for copper spot prices. (See table 3.6)

3.4.1.2 Chinese and overseas futures metal markets

From Figure 3.2, irregular peaks can also be found in these six metal futures time series. The eminent volatility clustering shows the existence of conditional heteroskedasticity. Table 3.3 reports the results of the augmented Dicky–Fuller test for stationarity for the six series. The results indicate that the null hypothesis (there exists a unit root) is rejected under the 1% significance level. Therefore, the six series are stationary.

Using methods similar to those in section 3.4.1.1, I determine the order of ARCH and GARCH in the variance equation. To explore the volatility asymmetry featured in the futures time series, I adopt the T - GARCH model for the futures time series.

Insert table 3.7 to table 3.12 here

From table 3.7 to table 3.12, I can see that asymmetry factors are significant in both Chinese and overseas futures markets. In the Chinese metal futures market, the sign of the asymmetry factor is positive for copper and zinc futures, and it is negative for aluminium futures. Therefore, although the mechanism of buying and selling is symmetrical in the futures market, the impacts of good and bad news on market volatility is still asymmetric. For copper and zinc futures, the impact of bad news is greater; for aluminium, the impact of good news is greater. In the Chinese futures market, people prefer to take long positions in speculative copper and zinc products for psychological reasons (Liu, Cheng, Wang, Hong and Li, 2008). When the futures price increases, the number of speculators also grows. With risk increasing, the reaction to market uncertainty consequently become stronger. As for aluminium, excess supply has dampened its price for a long period of time. It is probable that any goods news could lead to a moderate rebound in price.

The sign of the asymmetry factor is different in the LME market, however. It is positive only for copper, while negative for both aluminium and zinc. The results show that the impacts of good and bad news on market volatility are also asymmetric. A closer watch could tell that the sign of the asymmetry factor is identical for both aluminium and copper in the SHFE and the LME.

3.4.1.3 Overseas financial market—the AUDUSD rate and the ASX stock index

From Figure 3.2, irregular peaks could also be found in these two time series. Volatility clustering shows the existence of conditional heteroskedasticity. Table 3.4 reports the results of the augmented Dicky–Fuller test for stationarity for the two series. The results indicate that the null hypothesis (there exists a unit root) is rejected under a 1% significance level. Therefore, the two series are stationary.

Using the methods similar to those in section 3.4.1.1, I determine the order of ARCH and GARCH in the variance equation. Because taking short positions is allowed in the foreign exchange market, I adopt the TGARCH model for the AUDUSD time series. For ASX stock index, I choose to use GARCH model.

Insert table 3.13 to table 3.14 here

From table 3.13, I can see that asymmetry factors are significant in the AUDUSD time series and that the sign of the factor is positive, indicating that the impact of bad news is greater than that of good news for the AUDUSD. It is worth mentioning that the sign of the asymmetrical factor is identical for the SHFE copper and zinc futures and the AUDUSD.

3.4.2 VaR (Value-at-risk) test

Based on equations 5 and 6, I calculate the upside and downside VaR for all of the time series mentioned in section 3.4.1. The volatility used in the upside and downside

VaR is consistent with the model introduced in the previous section. For spot metal prices and the ASX stock index, the AR-GARCH model is adopted; for futures metal prices, the AUDUSD rate and AR-TGARCH model is adopted.

3.4.2.1 Chinese spot metal market--copper spot prices

From Figure 3.4, I could see that the upside and downside VaR model fit well for copper spot prices. For spot copper, it can be seen from table 3.15 that Kupiec's (1995) LR tests of downside and upside VaR are insignificant at conventional significance levels, suggesting the adequacy of the VaR model for the series.

Insert Figure 3.4 here

Insert table 3.15 here

It can be found in table 3.15 that the failure rate (the odds that the actual value exceeds the estimated upside and downside VaR values) in the downside is higher than that in the upside. The downside VaR has been crossed 82 times, 21 times more than the upside VaR. One probable reason for this result is that things could have turned out to be even worse than the worst scenario predicted by people when bad news came.

Comparing table 3.15 with table 3.17 (or see Figure 3.7), I find that the VaR of the futures market is larger than that of the spot market, indicating that the futures market is much riskier due to the participation of many speculators and their use of leverage.

3.4.2.2 Chinese and overseas futures metal market—the SHFE and the LME aluminium, copper and zinc prices

From figure 3.5 and table 3.16 to table 3.21, I can see that the upside and downside VaR models fit well for all of the futures time series. For the SHFE and LME futures market, Kupiec's (1995) LR tests of downside and upside VaR are all insignificant at conventional significance levels, suggesting the adequacy of the VaR model for all six

of these series.

Insert Figure 3.5 here

Insert table 3.16 to 3.21 here

Similar to the observation in the spot copper market, I could also find in tables 3.16 to 3.21 that the failure rate (the odds that the actual value exceeds the estimated upside and downside VaR value) in the downside is higher than that in the upside for all of the futures products, regardless which market they belong to. In the SHFE market, copper futures are the most typical example. The downside VaR has been crossed 87 times, 37 more times than the upside VaR. It is often the case that such a “cross” occurs in clusters, especially when market is in turmoil. Here is an example: during the 2008 global financial crisis, the downside VaR was surpassed on three consecutive days, from 2008.10.6 to 2008.10.8. These findings conform to what I observe during the financial crisis period. After the Lehman bankruptcy, panic permeated in the global market, triggering a vicious cycle: asset prices fell, followed by margin calls and a liquidity squeeze, followed by asset fire sales to meet the need, followed by a deeper fall in asset price. Under these circumstances, the VaR threshold calculated is crossed consecutively because a small probability event occurs and ferments. Unless dramatic measures are taken to stop the vicious cycle, this cycle will only repeat. When the market is tranquil, however, the upside and downside VaR is rarely crossed.

In the LME market, though, although the downside VaR is crossed more often than the upside VaR, the difference is narrower than that in the SHFE market. The probable reason is that in the SHFE market, they are trading using an “up and floor” mechanism to prevent prices from extremes, while in LME market, there is no similar arrangement. Hence, extreme market movement can be fulfilled in one day in the LME market, while in the SHFE, it may take several days.

Comparing table 3.16 with table 3.19, table 3.17 with table 3.20, and table 3.18 with

table 3.21 (or see Figure 3.8), I find that the mean level of VaR is higher in the LME market than in the SHFE market for aluminium and copper. However, the standard deviation is higher in the SHFE market for aluminium than it is in the LME market. A probable explanation for these findings is that market liquidity is better in the LME market than in the SHFE market because the LME market is open to all international investors, while the SHFE is more or less a domestic market and has less diverse participants.

3.4.2.3 Overseas financial market—the AUDUSD rate and the ASX stock index

From Figure 3.6 and table 3.22 to table 3.23, I see that the upside and downside VaR model fits well for the AUDUSD and ASX stock index time series. Moreover, Kupiec's (1995) LR tests of downside and upside VaR are insignificant at conventional significance levels, suggesting the adequacy of the VaR model for these two series.

Insert Figure 3.6 here

Insert table 3.22 to 3.23 here

Similar to the previous observation, I also find in tables 3.22 to 3.23 that the failure rate (the odds that the actual value exceeds the estimated upside and downside VaR values) in the downside is higher than that in the upside for these two series. For the AUDUSD time series, the downside VaR has been crossed 64 times, 26 more times than the upside VaR. For the ASX time series, the downside VaR has been crossed 66 times, 43 more times than the upside VaR. However, a closer watch on the data show that the crossings did not occur in clusters.

Comparing table 3.17 with tables 3.22 and 3.23 (or see Figure 3.10), I can see that the VaR of the SHFE futures market is larger than that of the foreign exchange market and the stock index market, indicating that the former has a larger risk. These findings are consistent with common sense because the futures market is characterized by

wider usage of leverage, while the foreign exchange market and stock index market are characterized by better market depth and liquidity.

3.4.3 Granger causality test

Table 3.24 shows the Granger causality empirical result. I try to analyse these results from three perspectives.

3.4.3.1 Chinese spot and futures metal market--copper spot and futures prices

Table 3.24 shows that at the 1% significance level, there is two-way Granger causality between the prices of the futures market and those of the spot market, with the impact of the futures market on the spot market being stronger than the impact of the spot market on the futures market. The results also hold in the upside and downside risk scenarios. The results indicate that in China's futures market, futures pricing functions effectively.

3.4.3.2 Chinese and overseas futures metal market—the SHFE and LME aluminium, copper and zinc prices

From Table 3.24, a causal link can be found between the SHFE and LME markets; with the direction being from the SHFE market to the LME market. Moreover, I could see that it is also the case in the extreme scenario (both upside risk and downside risk); an obvious causal link can be found from SHFE metal to LME metal (aluminium and copper hold at a 1% significance level while zinc holds at a 5% significance level.) These results indicate that under both normal and extreme market scenarios, the SHFE market can directly guide movement in the LME market, indicating the increase in China's pricing power for commodities from one perspective.

3.4.3.3 Chinese futures metal market and the overseas financial markets—the AUDUSD rate and the ASX stock index

From Table 3.24, I find that a causal link exists and the direction is from the ASX stock index to SHFE copper futures. However, the results do not hold in extreme scenarios (both upside and downside). The results suggest that unlike the SHFE and LME scenarios, the impact of China's domestic futures market on the global financial market is still limited. The "Chinese specific factor" should not be exaggerated.

3.5 Conclusion

In this Chapter, I try to explore the interaction between China's futures market and the overseas futures market. Specifically, I aim to study the information spillover effect between the domestic spot and futures markets as well as the information and risk spillover effects between the domestic futures market and the overseas futures market. Moreover, to check whether China has gained pricing power in the global commodity market, I also study the risk spillover effect between the domestic futures market and other overseas financial markets.

Hong and Cheng (2005) study the information spillover between China's domestic stock market and the global equity market. However, significant difference exists between the stock market and the futures market. Liu, Cheng, Wang, Hong and Li (2008) is an up-to-date piece of research in our field. This study takes the upside risk into account (short-seller's risk) rather than merely focusing on the downside risk. By investigating the interaction between the domestic and the overseas futures markets (which has never been done before) with a new data set, an extant research gap is filled. More importantly, I can check whether China has gained power in international commodity pricing from the perspective of the information and risk spillover effects.

The empirical results indicate that in China's futures market, futures pricing functions effectively because a two-way causal link is found between the spot and futures products, and the futures market plays the leading role. As the domestic futures market gradually matures, China has the potential to assume more pricing power in

the global market. As for the interaction between the domestic and overseas futures markets, a causal link exists from the SHFE market to LME market. Such results also hold for the extreme upside and downside risk scenarios. This result shows that movement in the SHFE market could directly guide movement in the LME market under any market scenario. To some extent, it also indicates that China's pricing power in the global commodity market has grown. As for the interaction between the SHFE metal market and the overseas financial market, no consistent conclusions have yet been found, indicating that the Chinese factor is largely reflected in the commodity market, while its impact on the global financial market as a whole is limited. For practitioners, these empirical results are of great practical importance. On the one hand, due emphasis should be laid on Chinese specific factors: both hedgers and speculators should make full use of the futures market. Hedgers could lock in the price by taking the opposite position in the futures market. Speculators could also try to exploit potential market mispricing opportunities between the domestic and the overseas futures market. On the other hand, Chinese specific factors should not be wildly exaggerated. Investment managers should be very careful when they try to exploit "mispricing opportunities" in overseas financial market (for example, stock markets) just based on their understanding of the domestic commodity market.

Figures and Tables in Chapter 3

Table 3.1: Descriptive statistics of the time series

	ALUM_F1	ALUM_FS1	ASX1	AUDUSD1	COPP_F1	COPP_FS1	LME_ALUM1	LME_COPP1	LME_ZINC1	ZINC_F1
Mean	-4.81E-05	-5.18E-05	0.000219	5.48E-05	0.000234	0.000225	4.65E-05	0.0002	0.000199	-0.000461
Median	0	0	0.000413	0.000271	0	0	0	0.000325	0	0.00057
Maximum	0.053988	0.043185	0.057244	0.081214	0.065999	0.06655	0.059131	0.118805	0.09135	0.059579
Minimum	-0.067094	-0.071925	-0.087043	-0.086048	-0.106115	-0.088375	-0.06581	-0.104003	-0.12138	-0.094029
Std. Dev.	0.009065	0.008492	0.009975	0.008272	0.013743	0.013018	0.012479	0.016722	0.017659	0.020787
Skewness	-0.67406	-0.668732	-0.540581	-0.557404	-0.447238	-0.354233	-0.206736	-0.182112	-0.267551	-0.398003
Kurtosis	10.21235	10.63669	10.0745	18.2296	7.276674	7.193532	5.505657	8.08151	7.233761	3.851288
Jarque-Bera	8557.598	9537.119	8141.439	37066.45	3032.928	2874.427	988.0829	3982.919	2793.122	52.12537
Probability	0	0	0	0	0	0	0	0	0	0
Sum	-0.183436	-0.197105	0.835219	0.209077	0.892956	0.857572	0.170928	0.737645	0.731922	-0.424903
Sum Sq. Dev.	0.313421	0.274516	0.379498	0.260947	0.719937	0.646232	0.572422	1.029636	1.147579	0.397541
Observations	3815	3808	3815	3815	3813	3814	3677	3683	3681	921

Note: ALUM_F1 refers to the SHFE aluminium futures rate of return; ALUM_FS1 refers to the Chinese spot aluminium futures rate of return; ASX refers to the ASX stock index rate of return; AUDUSD refers to the Australian dollar-dollar rate of return; COPP_F1 refers to the SHFE copper futures rate of return; COPP_FS1 refers to the SHFE copper futures rate of return; LME ALUM refers to the LME aluminium futures rate of return; LME COPP refers to the LME copper futures rate of return; LME ZINC refers to the LME zinc futures rate of return; ZINC_F1 refers to the SHFE zinc futures rate of return;

The result of the stationary test

Table 3.2: The stationary tests for the Chinese spot metal market--copper spot rate of return

ADF test statistics (spot copper)	-31.45234	5% critical value -3.4129
10% critical value	-3.1285	

Table 3.3: The stationary tests for the Chinese and overseas futures metal market—SHFE and LME aluminium, copper and zinc rates of return

ADF test statistics (SHFE aluminium)	-61.31938	1% critical value -3.9644
ADF test statistics (SHFE copper)	-32.00709	5% critical value -3.4129
ADF test statistics (SHFE zinc)	-19.49676	10% critical value -3.1285
ADF test statistics (LME aluminium)	-63.35377	
ADF test statistics (LME copper)	-64.76101	
ADF test statistics (LME zinc)	-63.97524	

Note: SHFE aluminium, copper, and zinc refer to the Shanghai Futures Exchange aluminium, copper and zinc rates of return, respectively; LME aluminium, copper, and zinc refer to the London Metal Exchange aluminium, copper and zinc rates of return, respectively

Table 3.4: Stationary tests for the overseas financial market—the AUDUSD rate and the ASX stock index

ADF test statistics (AUDUSD)	-66.02937	1% critical value -3.9644
ADF test statistics (ASX)	-64.01139	5% critical value -3.4129
		10% critical value -3.1285

Note: AUDUSD refers to the Australian dollar-dollar rate, and ASX refers to the Australian stock index

The result of the AR-GARCH and AR-TGARCH models

Table 3.5: GARCH model for the SHFE aluminium spot rate of return

Mean equation	ALUM_FS1
ALUM_FS1(-1)	0.010811 (0.037483)
Variance equation	ALUM_FS1
C	0.003049 *** (0.0000)
RESID(-1)^2	0.096777 (0.1265)
GARCH(-1)	-0.005886 ** (0.0254)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; ALUM_FS1 refers to the Chinese spot aluminium rate of return

Table 3.6: GARCH model for Chinese copper spot rate of return

Mean equation	COPP_FS1
COPP_FS1 (-1)	0.080232 *** (0.0000)
Variance equation	COPP_FS1
C	1.48E-06 *** (0.0000)
RESID(-1)^2	0.073848 (0.0000)
GARCH(-1)	0.917144 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; COPP_FS1 refers to the SHFE copper futures rate of return

Table 3.7: TGARCH model for the SHFE aluminium futures rate of return

Mean equation	ALUM_F1
ALUM_F1(-5)	-0.029093 * (0.0496)
Variance equation	ALUM_F1
C	1.31E-06 *** (0.0000)
RESID(-1)^2	0.187444 *** (0.0000)
RESID(-1)^2 * (RESID(-1) < 0)	-0.037669 *** (0.0000)
GARCH(-1)	0.836915 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; ALUM_F1 refers to the SHFE aluminium futures rate of return

Table 3.8: TGARCH model for the SHFE copper futures rate of return

Mean equation	COPP_F1
COPP_F1(-2)	0.035023*(0.0321)
Variance equation	COPP_F1
C	1.71E-06 *** (0.0000)
RESID(-1)^2	0.071291 *** (0.0000)
RESID(-1)^2*(RESID(-1)<0)	0.017566*(0.0274)
GARCH(-1)	0.911362 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; COPP_F1 refers to the SHFE copper futures rate of return

Table 3.9: TGARCH model for the SHFE zinc futures rate of return

Mean equation	ZINC_F1
ZINC_F1(-2)	0.057223 (0.1086)
Variance equation	ZINC_F1
C	5.94E-05 *** (0.0023)
RESID(-1)^2	0.144422 *** (0.0000)
GARCH(-1)	0.720724 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; ZINC_F1 refers to the SHFE zinc futures rate of return

Table 3.10: TGARCH model for the LME aluminium futures rate of return

Mean equation	LME_ALUM1
LME_ALUM1 (-2)	-0.037231 (0.0235)
Variance equation	LME_ALUM1
C	1.12E-06 *** (0.0000)
RESID(-1)^2	0.051171 *** (0.0000)
RESID(-1)^2*(RESID(-1)<0)	-0.017493 *** (0.0017)
GARCH(-1)	0.720724 *** (0.0000)

Note: the statistics in parenthesis are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; LME_ALUM1 refers to the LME aluminium futures rate of return

Table 3.11: TGARCH model for the LME copper futures rate of return

Mean equation	LME_COPP1
LME_COPP1 (-5)	0.036424*(0.0325)
Variance equation	LME_COPP1
C	1.86E-06 *** (0.0000)
RESID(-1)^2	0.044202*** (0.0000)
RESID(-1)^2*(RESID(-1)<0)	0.010781*(0.0241)
GARCH(-1)	0.943265 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; LME_COPP1 refers to the LME copper futures rate of return

Table 3.12: TGARCH model for the LME zinc futures rate of return

Mean equation	LME_ZINC1
LME_ZINC1 (-2)	-0.065641*** (0.0001)
Variance equation	LME_ZINC1
C	4.17E-07 *** (0.0000)
RESID(-1)^2	0.042931*** (0.0000)
RESID(-1)^2*(RESID(-1)<0)	-0.024014*** (0.0000)
GARCH(-1)	0.968549 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; LME_ZINC1 refers to the LME zinc futures rate of return

Table 3.13: TGARCH model for the AUDUSD rate of return

Mean equation	AUDUSD1
AUDUSD1 (-1)	-0.031148(0.0585)
Variance equation	AUDUSD1
C	5.76E-07 *** (0.0000)
RESID(-1)^2	0.044051*** (0.0000)
RESID(-1)^2*(RESID(-1)<0)	0.013694** (0.0456)
GARCH(-1)	0.939201 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; AUDUSD1 refers to the Australian dollar–dollar rate of return

Table 3.14: GARCH model for the ASX stock index rate of return

Mean equation	ASX1
ASX1 (-3)	-0.031148*(0.0585)
Variance equation	ASX1
C	1.24E-06 *** (0.0000)
RESID(-1)^2	0.092459*** (0.0000)
GARCH(-1)	0.895763 *** (0.0000)

Note: the statistics in parentheses are t-statistics. One, two, and three asterisks indicate the 10%, 5% and 1% levels of statistical significance; ASX1 refers to the ASX stock index rate of return

Backtesting results:**Table 3.15: Backtesting result of the downside and upside VaR for the Chinese copper spot rate of return**

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.027	0.013	82	2.15%	1.91
Upside VaR	99	0.027	0.013	61	1.60%	1.96

Table 3.16: Backtesting result of the downside and upside VaR for the SHFE aluminium futures rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.019	0.011	80	2.10%	1.91
Upside VaR	99	0.019	0.011	70	1.84%	1.94

Table 3.17: Backtesting result of the downside and upside VaR for the SHFE copper futures rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.029	0.014	87	2.28%	1.89
Upside VaR	99	0.029	0.014	50	1.31%	1.99

Table 3.18: Backtesting result of the downside and upside VaR for the SHFE zinc futures rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.048	0.009	12	1.31%	1.99
Upside VaR	99	0.047	0.009	9	0.98%	2.01

Table 3.19: Backtesting result of the downside and upside VaR for the LME aluminium futures rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.028	0.009	55	1.44%	1.98
Upside VaR	99	0.028	0.009	51	1.34%	1.99

Table 3.20: Backtesting result of the downside and upside VaR for the LME copper futures rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.035	0.015	58	1.52%	1.97
Upside VaR	99	0.036	0.015	51	1.34%	1.99

Table 3.21: Backtesting result of the downside and upside VaR for the LME zinc futures rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.037	0.017	59	1.55%	1.97
Upside VaR	99	0.037	0.017	51	1.34%	1.99

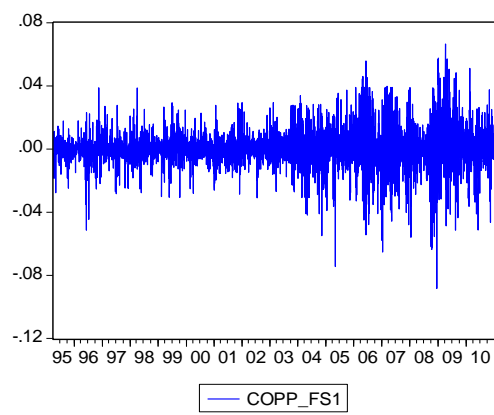
Table 3.22: Backtesting result of the downside and upside VaR for the AUDUSD rate of return

GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.017	0.008	64	1.68%	1.96
Upside VaR	99	0.017	0.008	38	1.00%	2.00

Table 3.23: Backtesting result of the downside and upside VaR for the ASX stock index rate of return

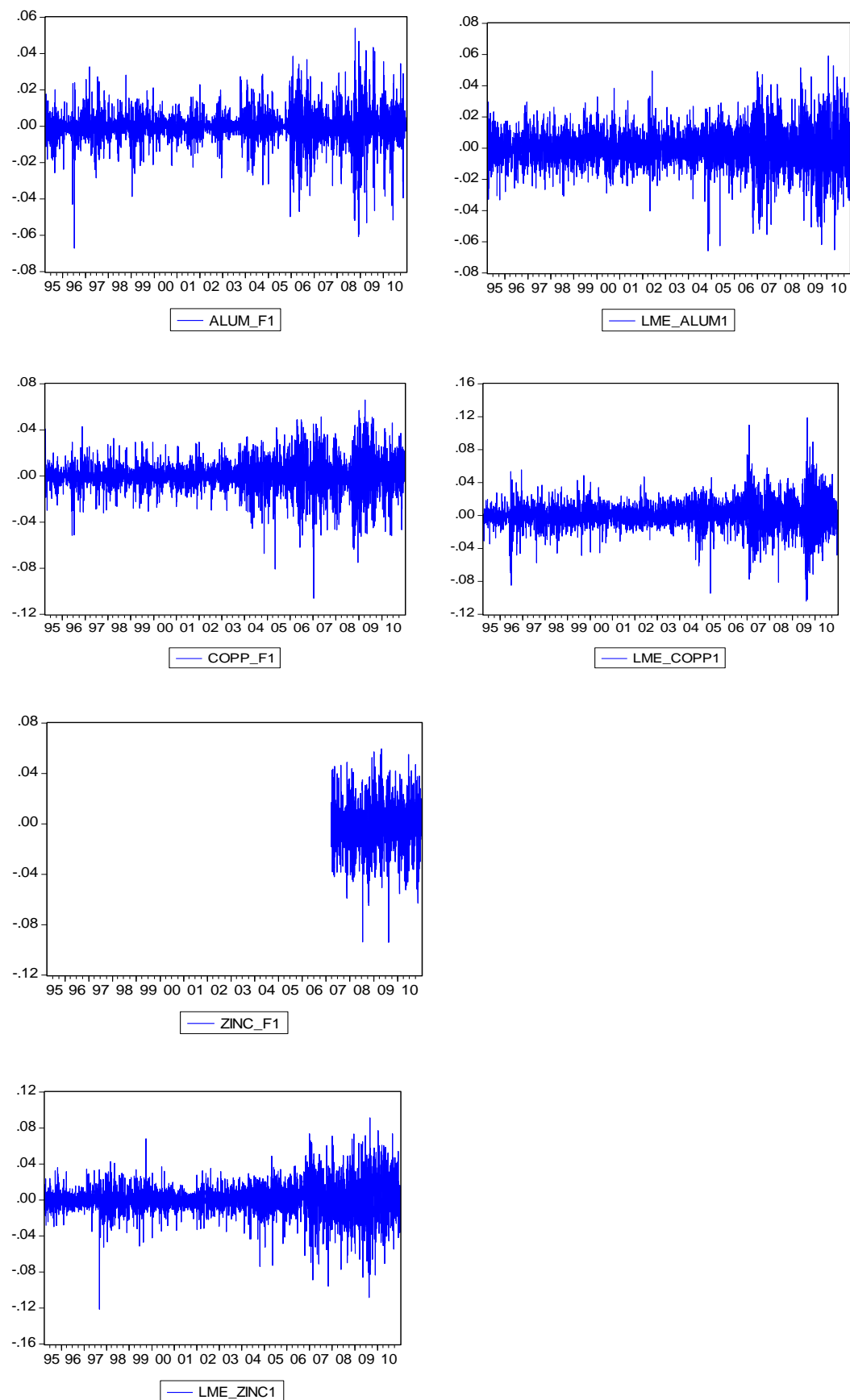
GARCH model	Confidence level (%)	Mean	Std.dev.	Failure time	Failure rate	LR statistics
Downside VaR	99	-0.021	0.010	66	1.73%	1.95
Upside VaR	99	0.021	0.010	23	0.60%	1.95

Figure 3.1: Chinese spot metal market-copper spot rate of return



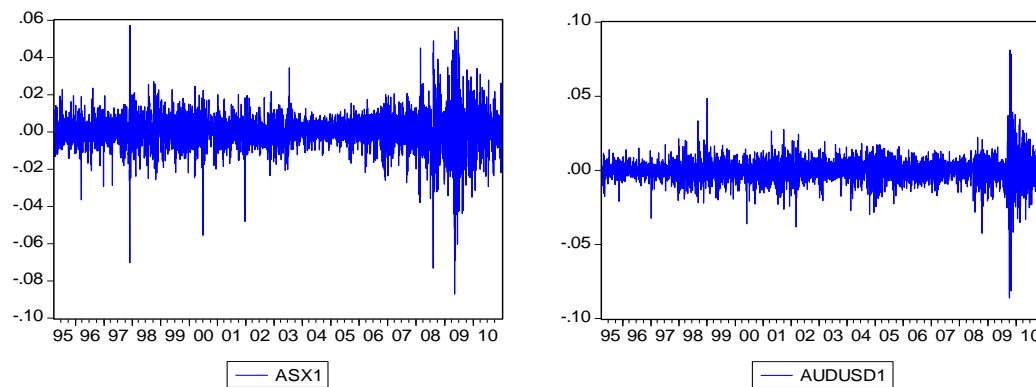
Note: COPP_FS1 refers to the SHFE copper spot rate of return

Figure 3.2: Chinese and overseas futures metal market--SHFE and LME aluminium, copper and zinc rates of return



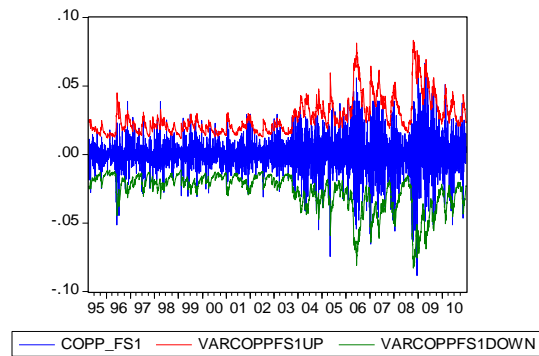
Note: ALUM_F1 refers to the SHFE aluminium futures rate of return; COPP_F1 refers to the SHFE copper futures rate of return; ZINC_F1 refers to the SHFE zinc futures rate of return; LME ALUM refers to the LME aluminium futures rate of return; LME COPP refers to the LME copper futures rate of return; LME ZINC refers to the LME zinc futures rate of return

Figure 3.3: Overseas financial market—the AUDUSD rate and the ASX stock index



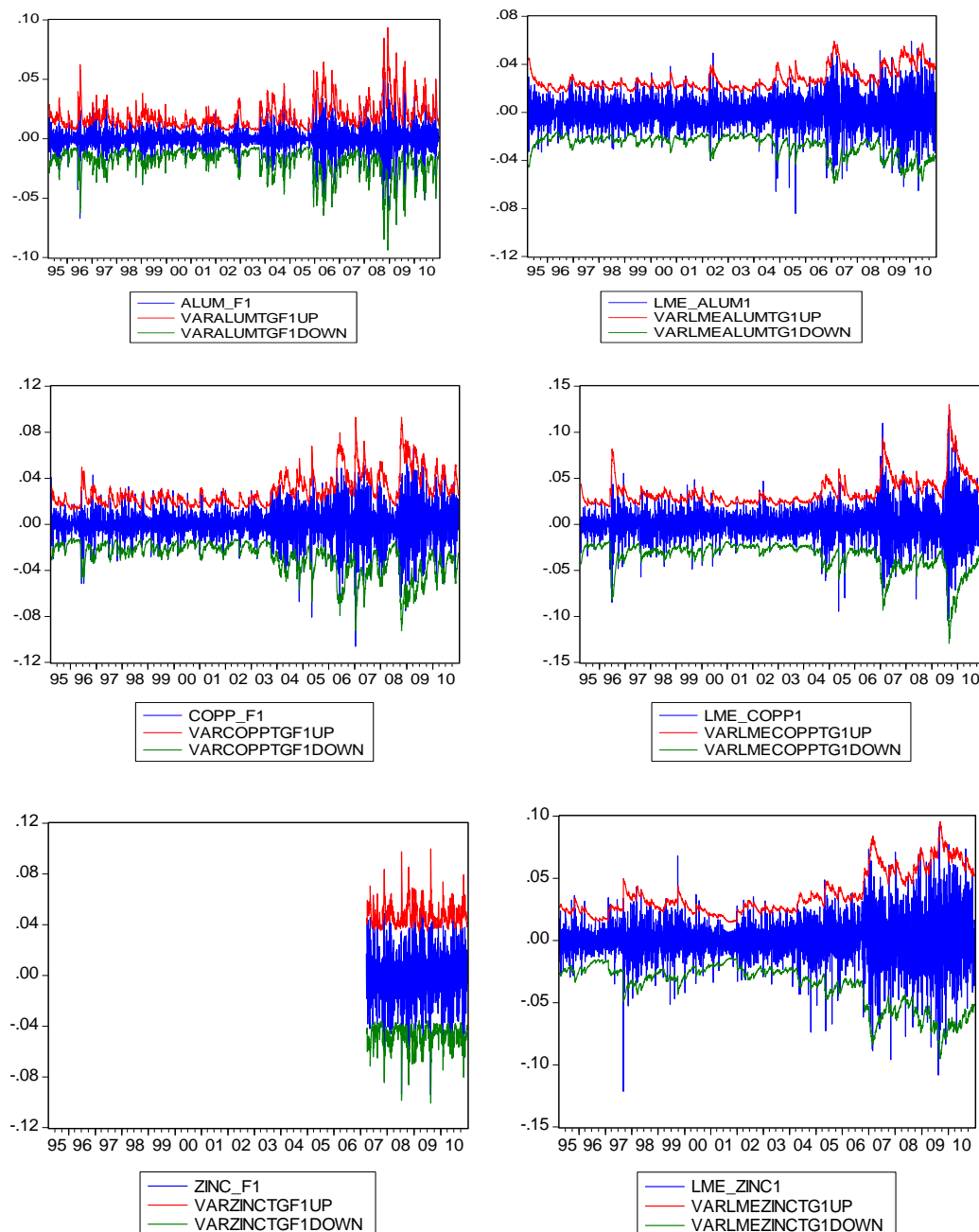
Note: ASX1 refers to the ASX stock index rate of return; AUDUSD1 refers to the Australian dollar–dollar rate of return

Figure 3.4: Chinese spot metal market--copper spot rate of return-upside VaR and downside VaR



Note: COPP_FS1 refers to the SHFE copper spot rate of return; VARCOPPFS1UP refers to the upside VaR of the SHFE copper spot rate of return; VARCOPPFS1DOWN refers to the downside VaR of the SHFE copper spot rate of return

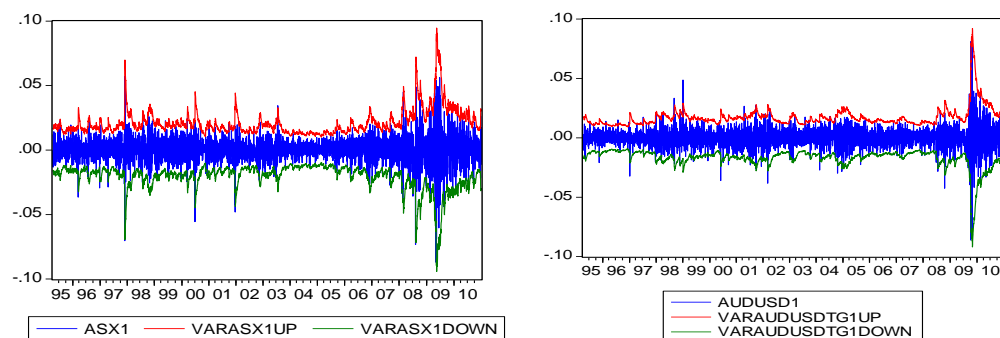
Figure 3.5: Chinese and overseas futures metal markets—the SHFE and LME aluminium, copper and zinc rates of return



Note: ALUM_F1 refers to the SHFE aluminium futures rate of return; COPP_F1 refers to the SHFE copper futures rate of return; ZINC_F1 refers to the SHFE zinc futures rate of return; LME ALUM refers to the LME aluminium futures rate of return; LME COPP refers to the LME copper futures rate of return; LME ZINC refers to the LME zinc futures rate of return; VARALUMTG1UP refers to the upside VaR of the SHFE aluminium futures rate of return; VARALUMTG1DOWN refers to the downside VaR of the SHFE aluminium futures rate of return; VARCOPPTG1UP refers to the upside VaR of the SHFE copper futures rate of return; VARCOPPTG1DOWN refers to the downside VaR of the SHFE copper futures rate of return; VARZINCTG1UP refers to the upside VaR of the SHFE zinc futures rate of

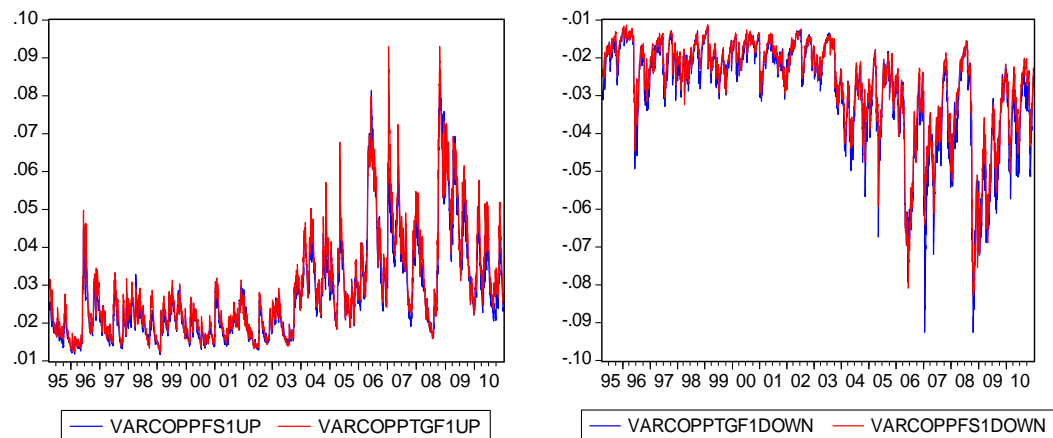
return; VARZINCTG1DOWN refers to the downside VaR of the SHFE zinc futures rate of return; VARLMEALUMTG1UP refers to the upside VaR of the LME aluminium futures rate of return; VARALUMTG1DOWN refers to the downside VaR of the LME aluminium futures rate of return; VARLMECOPPTG1UP refers to the upside VaR of the LME copper futures rate of return; VARCOPPTG1DOWN refers to the downside VaR of the LME copper futures rate of return; VARLMEZINCTG1UP refers to the upside VaR of the LME zinc futures rate of return; VARZINCTG1DOWN refers to the downside VaR of the LME zinc futures rate of return

Figure 3.6: Overseas financial market—the AUDUSD rate and the ASX stock index



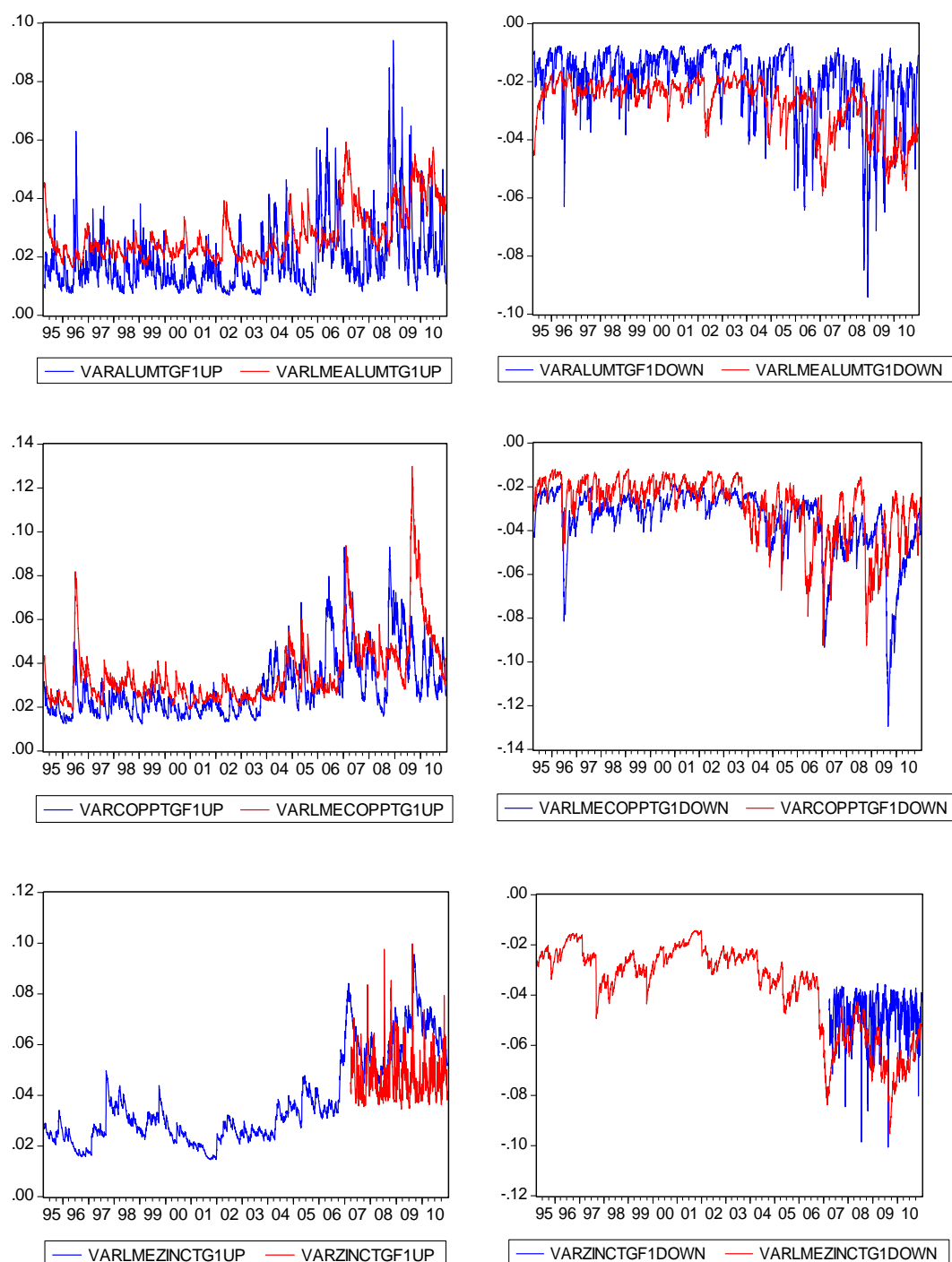
Note: ASX1 refers to the ASX stock index rate of return; AUDUSD1 refers to the Australian dollar–dollar rate of return; VARASX1UP refers to the upside VaR of the ASX stock index rate of return; VARASX1DOWN refers to the downside VaR of the ASX stock index rate of return; VARAUDUSD1UP refers to the upside VaR of the AUDUSD rate of return; VARAUDUSD1DOWN refers to the downside VaR of the AUDUSD rate of return

Figure 3.7: Comparison between Chinese spot and futures copper rates of return: upside and downside VaR



Note: VARCOPPFS1UP refers to the upside VaR of the SHFE copper futures rate of return; VARCOPPFS1DOWN refers to the downside VaR of the SHFE copper futures rate of return; VARCOPPTGF1UP refers to the upside VaR of the SHFE copper futures rate of return; VARCOPPTGF1DOWN refers to the downside VaR of the SHFE copper futures rate of return

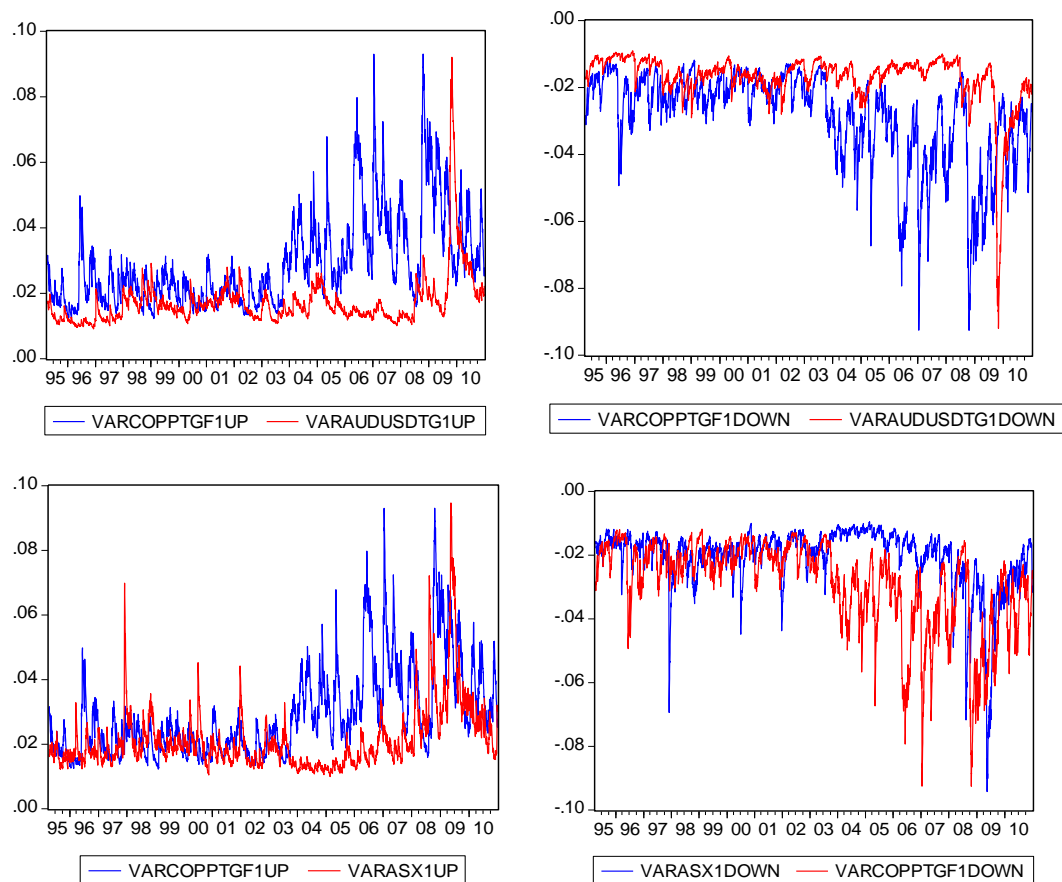
Figure 3.8: Comparison between the SHFE and the LME futures rates of return—aluminium, copper and zinc: upside and downside VaR



Note: VARALUMTG1UP refers to the upside VaR of the SHFE aluminium futures rate of return; VARALUMTG1DOWN refers to the downside VaR of the SHFE aluminium futures rate of return; VARCOPPTG1UP refers to the upside VaR of the SHFE copper futures rate of return; VARCOPPTG1DOWN refers to the downside VaR of the SHFE copper futures rate of return; VARZINCTG1UP refers to the upside VaR of the SHFE zinc futures rate of return; VARZINCTG1DOWN refers to the

downside VaR of the SHFE zinc futures rate of return; VARLMEALUMTG1UP refers to the upside VaR of the LME aluminium futures rate of return; VARALUMTG1DOWN refers to the downside VaR of the LME aluminium futures rate of return; VARLMECOPPTG1UP refers to the upside VaR of the LME copper futures rate of return; VARCOPPTG1DOWN refers to the downside VaR of the LME copper futures rate of return; VARLMEZINCTG1UP refers to the upside VaR of the LME zinc futures rate of return; VARZINCTG1DOWN refers to the downside VaR of the LME zinc futures rate of return

Figure 3.9: Comparison between the SHFE copper futures rate of return and the AUDUSD and ASX stock index rates of return: upside and downside VaR



Note: VARPPTGF1UP refers to the upside VaR of the SHFE copper futures rate of return; VARPPTGF1DOWN refers to the downside VaR of the SHFE copper futures rate of return; VARASX1UP refers to the upside VaR of the ASX stock index rate of return; VARASX1DOWN refers to the downside VaR of the ASX stock index rate of return; VARAUDUSDTG1UP refers to the upside VaR of the AUDUSD rate of return; VARAUDUSDTG1DOWN refers to the downside VaR of the AUDUSD rate of return

Table 3.24 Granger causality test result using the entire sample

X1	X2	Test 1	Test 2
COPP_F1	COPP_FS1	151.141 (0.0000)	3.75790(0.02342)
ALUM_F1	LME_ALUM1	4.44037(0.01185)	0.17125(0.84261)
COPP_F1	LME_COPP1	3.69339(0.02498)	0.49668(0.60859)
ZINC_F1	LME_ZINC1	4.58778(0.01041)	0.49299(0.61096)
COPP_F1	AUDUSD1	1.39140(0.24885)	2.16236(0.11519)
COPP_F1	ASX1	1.51856(0.21916)	7.34576(0.00065)
VARCOPPF1UP	VARCOPPTGF1UP	6.69528(0.00125)	6.58140(0.00140)
VARCOPPF1DOWN	VARCOPPTGF1DOWN	6.69528(0.00125)	6.58140(0.00140)
VARALUMTG1UP	VARLMEALUMTG1UP	6.32997(0.00180)	0.98211(0.37461)
VARALUMTG1DOWN	VARLMEALUMTG1DOWN	6.32997(0.00180)	0.98211(0.37461)
VARCOPPTGF1UP	VARLMECOPPTG1UP	10.1483 (0.0000)	3.12039(0.04425)
VARCOPPTGF1DOWN	VARLMECOPPTG1DOWN	10.1483 (0.0000)	3.12039(0.04425)
VARZINCTG1UP	VARLMEZINCTG1UP	4.35426(0.01312)	0.68530(0.50420)
VARZINCTG1DOWN	VARLMEZINCTG1DOWN	4.35426(0.01312)	0.68530(0.50420)
VARCOPPTGF1UP	VARAUDUSD1UP	2.07056(0.12626)	0.27004(0.76336)
VARCOPPTGF1DOWN	VARAUDUSD1DOWN	2.07056(0.12626)	0.27004(0.76336)
VARCOPPTGF1UP	VARASX1UP	1.51120(0.22078)	1.30134(0.27229)
VARCOPPTGF1DOWN	VARASX1DOWN	1.51120(0.22078)	1.30134(0.27229)

Note: COPP_FS1 refers to the SHFE copper futures rate of return; ALUM_F1 refers to the SHFE aluminium futures rate of return; COPP_F1 refers to the SHFE copper futures rate of return; ZINC_F1 refers to the SHFE zinc futures rate of return; LME ALUM1 refers to the LME aluminium futures rate of return; LME COPP refers to the LME copper futures rate of return; LME ZINC refers to the LME zinc futures rate of return; ASX1 refers to the ASX stock index rate of return; AUDUSD1 refers to the Australian dollar–dollar rate of return; VARCOPPF1UP refers to the upside VaR of the SHFE copper futures rate of return; VARCOPPF1DOWN refers to the downside VaR of the SHFE copper futures rate of return; VARALUMTG1UP refers to the upside VaR of the SHFE aluminium futures rate of return; VARALUMTG1DOWN refers to the downside VaR of the SHFE aluminium futures rate of return; VARCOPPTG1UP refers to the upside VaR of the SHFE copper futures rate of return; VARCOPPTG1DOWN refers to the downside VaR of the SHFE copper futures rate of return; VARZINCTG1UP refers to the upside VaR of the SHFE zinc futures rate of return; VARZINCTG1DOWN refers to the downside VaR of the SHFE zinc futures rate of return; VARLMEALUMTG1UP refers to the upside VaR of the LME aluminium futures rate of return; VARALUMTG1DOWN refers to the downside VaR of the LME aluminium futures rate of return; VARLMECOPPTG1UP refers to the upside VaR of the LME copper futures rate of return; VARCOPPTG1DOWN refers to the downside VaR of the LME copper futures rate of return; VARLMEZINCTG1UP refers to the upside VaR of the LME zinc futures rate of return; VARZINCTG1DOWN refers to the downside VaR of the LME zinc futures rate of return; VARASX1UP refers to the upside VaR of the ASX stock index rate of

return; VARASX1DOWN refers to the downside VaR of the ASX stock index rate of return; VARAUDUSD1UP refers to the upside VaR of the AUDUSD rate of return; VARAUDUSD1DOWN refers to the downside VaR of the AUDUSD rate of return

Chapter 4 The application of dynamic commodity futures timing strategies in the context of China's market

4.1 Introduction

In the previous chapters, I investigate how the commodity futures price interacts with domestic macroeconomic variables and overseas futures prices. These findings lay a good foundation for what I intend to achieve in this chapter: forming an effective dynamic timing strategy in China's commodity market with full consideration of Chinese specific factors.

According to Abanomey and Mathur (2001), Georgiev (2001), Kaplan and Lummer (1998), commodities serve as good diversifiers when added to a traditional asset portfolio. Edwards and Caglayan (2001) showed that commodity funds have higher returns during bearish stock markets along with a lower correlation. Meanwhile, Pesaran and Timmermann (1995) and Bauer, Derwall and Molenaar (2004) showed that well-specified dynamic timing strategies could generate better performance than a pure "buy-and-hold" strategy for some assets, such as stocks. Hence, it is natural to ask whether the dynamic timing strategy could beat a "buy-and-hold" strategy for commodity futures in China.

In this chapter, I adopt Vrugt, Bauer and Molenaar's (2004) dynamic modelling approach to predict the sign of the monthly returns of the three metal futures listed on the Shanghai Futures Exchange: copper, aluminium and zinc. Following Vrugt, Bauer and Molenaar (2004), the base set of explanatory variables is classified into three categories: 1) Business cycle indicators; 2) Monetary environment indicators; 3) Indicators on the market sentiment.

These three categories have been used predominantly in studies investigating the

relationship between the macroeconomy and traditional asset classes or in timing studies, such as Pesaran and Timmermann (1995). However, this type of research framework has not been well applied in non-traditional asset classes, such as commodity futures, let alone applied to commodity futures in China. Here, variables in each category should be gathered with full consideration of “Chinese specific factors”. Thus, my findings from the previous two chapters can offer great help. As for the data, it is taken from the Chinese financial database – Wind **system**. All of the series used are stylized in monthly terms. Due to data availability and issues of practicality, all of the independent variables are lagged one month.

Econometrically, the approach involves a recursive estimation procedure that allows for continuous permutations among the determinants in accordance with a predefined model selection criterion. During the in-sample period, I estimate parameters for these models using standard Ordinary Least Squares (OLS). Following this procedure, each model generates monthly signals during a 12-month training period. Then, at the end of the training period, I rank all models using the realized information ratios. The strategy is to use the model with the highest realized information ratio to forecast the sign of the next month’s metal futures return. Finally, in the out-of-sample trading period, futures on the metal futures market are bought or sold dependent on the signal.

This chapter extends the knowledge of dynamic timing strategies in following ways. First, this chapter focuses on China’s commodity futures, an asset class not studied previously. Second, although Vrugt, Bauer and Molenaar’s framework is applied, the variables are chosen considering “Chinese specific factors”. Industrial growth, monetary growth, and the foreign exchange rate are gathered based on findings from Chapter 2; the lagged LME return data are collected based on findings in Chapter 3.

The empirical results indicate that factor inclusion does vary across the entire sample period for all three metals. All three metal futures record good performance, and zinc’s performance is particularly impressive. The dynamic modelling approach could

provide a better information ratio than the pure “buy-and-hold” strategy, demonstrating that a dynamic timing strategy does perform better. Meanwhile, the economic intuition concern does not pose a problem.

The remainder of this chapter is organized as follows: section 4.2 introduces the consulted literature. Section 4.3 gives a description of the variables chosen and the methodology adopted. Then, the empirical results are presented in section 4.4. Finally, section 4.5 concludes the chapter.

4.2 Literature review

4.2.1 Tactical asset allocation with commodities

Many researchers have argued that commodities serve as good diversifiers: no or a less-than-proportional portfolio return is sacrificed, while the overall portfolio risk is reduced. (Abanomey and Mathur (2001), Georgiev (2001), Kaplan and Lummer (1998)) Edwards and Caglayan (2001) show that commodity funds have higher returns during bearish stock markets, along with a lower correlation. Related to this finding, Chow (1999) provide evidence that commodities perform well when the general financial market climate is negative. Furthermore, commodities appear to serve as a possible hedge against inflation, see Bodie (1983), Froot (1995) and Gorton and Rouwenhorst (2004), which makes them even more attractive to entities with fixed liabilities in real terms, such as pension funds. Nijman and Swinkels (2003) show that commodity investments are beneficial to pension funds within a mean variance framework.

Based on these studies, institutional investors are increasingly integrating commodities in their strategic asset allocation, predominantly in a passive fashion. Although the literature on the strategic benefits of investing in commodities is growing, papers on tactical asset allocation with commodities are quite difficult to find. Notable exceptions are the work of Johnson and Jensen (2001) and Jensen,

Johnson and Mercer (2002), in which the allocation of commodities is conditioned on the monetary environment. Furthermore, Nijman and Swinkels (2003) examined a tactical switching strategy between commodities and stocks. Most of these studies use a small set of predetermined explanatory variables as the basis for their tactical decisions. Erb and Harvey (2006) found that the prospective annualized excess return of a rebalanced portfolio of commodity futures can be “equity-like”. Certain security characteristics, such as the term structure of futures prices, and some portfolio strategies have historically been rewarded with above average returns. These authors note that it is important to avoid naïve extrapolation of historical returns and to strike a balance between dependable sources of returns and potential sources of returns.

4.2.2 Dynamic timing strategies

Pesaran and Timmermann (1995) examine the robustness of the evidence on the predictability of US stock returns and address the issue of whether this predictability could have been historically exploited by investors to earn profits in excess of a pure “buy-and-hold” strategy in the market index. They concluded that the predictive power of various economic factors for stock returns changes over time and tends to vary with the volatility of returns. The extent to which stock returns were predictable appeared to be quite low in the relatively tranquil markets of the 1960s, but increased to a level where, net of transaction costs, it could have been exploited by investors in the volatile markets of the 1970s.

Li and Lam (2002) consider optimal market-timing strategies under transaction costs. They assume that an asset’s return follows an autoregressive model and use long-term investment growth as the objective of a market-timing strategy that entails shifting funds between a risky asset and a riskless asset. They give the optimal trading strategy for a finite investment horizon and analyse its limiting behaviour. For a finite horizon, the optimal decision in each step depends on two threshold values. If the return value today falls within the interval, nothing needs to be done; otherwise, funds are shifted from one asset to the other, depending on which threshold value is exceeded. When

the investment horizon tends to infinity, the optimal strategy converges to a stationary policy, which is shown to be closely related to a well-known technical trading rule called the Momentum Index Trading Rule. An integral equation of the two threshold values is given, and numerical results for the limiting stationary strategy are presented. The results confirm the obvious guess that the no-transaction region increases as transaction costs increase. Finally, the limiting stationary strategy is applied to data from the Hang Seng Index Futures market in Hong Kong. The out-of-sample performance of the limiting stationary strategy is found to be better than the simple strategy used in the literature, which is based on a 1-step-ahead forecast of return.

Bauer, Derwall and Molenaar (2004) examined whether short-term variation in the Japanese size and value premium is sufficiently predictable to be exploited by a timing strategy. In the spirit of Pesaran and Timmermann (1995), they employ a dynamic modelling approach in which they explicitly allow for permutations among the determinants in order to mitigate typical data-snooping biases. Using a base set of candidate regression factors; they perform an in-sample estimation of all economically sensible models. Subsequently, a “most suitable” model is determined according to a selection criterion. However, whereas most studies use in-sample model selection criteria, they also introduce an out-of-sample training period to select the models. Then, they implement their strategy in a second-stage out-of-sample period: the trading period. All stages reoccur on a monthly basis via a rolling window framework. The results confirm sufficient predictability under lower transaction cost levels. Under high transaction cost scenarios, however, it is more difficult to obtain incremental benefits.

Vrugt, Bauer and Molenaar (2004) investigated timing strategies with commodity futures using factors directly related to the status of the business cycle, the monetary environment and the sentiment of the market. They use a dynamic model selection procedure in the spirit of the recursive modelling approach of Pesaran and Timmermann (1995). However, instead of using in-sample model selection criteria,

they build on the extensions of Bauer, Derwall and Molenaar (2004) by introducing an out-of-sample model training period to select the optimal models. The best models from this training period are used to generate forecasts for the subsequent trading period. Their results indicate that the variation in commodity futures returns is sufficiently predictable to be exploited by a realistic timing strategy.

Brooks, Katsaris and Persaud (2005) investigated the relative profitability of several different methodologies using a very long dataset on the S&P 500. To overcome the accusations of data snooping and arbitrary parameter choices that beset much of the previous work in this area, they carefully consider whether the rule performance is sensitive to the specified user-adjustable parameters. They find that all but one of the approaches are able to beat a “buy-and-hold” equities strategy in risk adjusted terms, although a strategy based on the difference between the price-earnings ratio and short-term treasury yields works best.

Bhaduri and Saraogi (2010) examined the relationship between yield spread and stock market returns. They also explore a dynamic trading strategy of timing the Indian stock market using the yield spread as an indicator variable. The study concluded with the important result that the yield spread is successful in identifying points of entry and exit for the Indian stock market, thereby delivering superior returns compared to a conventional “buy-and-hold” strategy.

According to the literature consulted, commodities serve as good diversifiers when added to a traditional asset portfolio; meanwhile, well-specified dynamic timing strategies could generate better performance than a pure “buy-and-hold” strategy for some assets. For practitioners such as asset managers, the most convenient way to obtain exposure in commodities is to participate in the commodity futures market. Therefore, it is natural to ask whether a dynamic timing strategy could work for commodity futures in China. Thus, I lay the hypothesis of the empirical test as follows:

dynamic timing strategies could provide excess returns over pure “buy-and-hold” strategies in the Chinese commodities futures market.

4.3 Data specification and methodology

4.3.1 Data specification

In this chapter, I adopt Vrugt, Bauer and Molenaar’s (2004) dynamic modelling approach to predict the sign of the monthly returns of the three metal futures listed on the Shanghai Futures Exchange: copper, aluminium and zinc. In chapter 4, simple returns are used because this is common practice for commodity futures practitioners such as traders and investors. Here, the monthly return R_t is defined as follows:

$$R_t = (F_t - F_{t-1}) / F_{t-1} \quad 4.1$$

As done by Vrugt, Bauer and Molenaar (2004), the base set of explanatory variables is classified into three categories:

- (1) Business cycle indicators;
- (2) Monetary environment indicators;
- (3) Indicators of market sentiment.

These three categories have been used predominantly in studies investigating the relationship between the macroeconomy and traditional asset classes or in timing studies, such as Pesaran and Timmermann (1995). However, this type of research framework has not been well applied to non-traditional asset classes, such as commodities, let alone to commodities in China. Here, variables in each category are gathered with consideration of “Chinese specific factors”. Then, my findings from the previous two chapters can offer great help.

4.3.1.1 Business cycle indicators

I choose the variable industrial growth with respect to the category of business cycle indicators, and many other variables are eliminated. Many scholars have chosen to use other qualified candidates to detect their timing skills. However, these variables may not be suitable in China due to data availability or authenticity concerns. Chen (1991) shows that the dividend yield and the default spread are (inversely) related to current business cycle conditions. However, such variables could not be easily constructed in China. On the one hand, because Chinese firms have no tradition of paying dividends, the dividend yield is not a widely accepted variable; on the other hand, bankruptcy is a rarity in China, and the credit rating offers little information to determine the credit status of firms issuing bonds. Hence, these two variables are eliminated. Chen shows the difference in yields between a constant maturity 10-Year T-bond and a constant maturity 3-month T-bill – namely, term spreads are related to more distant business cycle conditions. Although data quality for the 10-year T-bond is quite good, data quality for the 3-month T-bill is not ideal because 3-month T-bills are not actively traded in China's bond market. Hence, the difference in yields is also not suitable. Moreover, Chen finds a positive link between the business cycle, annual production growth and GNP (and consumption). In chapter 2, industrial growth is chosen as the variable to measure economic activity. Similarly, I include the change in year-on-year industrial production here as the variable.

4.3.1.2 Monetary environment indicator

Froot (1995), Strongin and Petsch (1996), Jensen, Johnson and Mercer (2002) and Gorton and Rouwenhorst (2004) explicitly document the inflation-hedging properties of commodities. Commodities could possibly hedge against the rise of inflation. To capture this insight, I include the year-on-year rate of inflation. Jensen, Johnson and Mercer (2002) show that the monetary environment is helpful for discriminating between good and bad commodity performance. In China, however, the monetary

supply is more critical than the monetary price (the interest rate) most of the time. Fan, Yu and Zhang (2010) investigates the responsiveness of the Chinese government's monetary policies, in terms of the money supply and interest rates, to economic conditions and the effectiveness of these policies in achieving the goals of stimulating economic growth and controlling inflation. He finds that the money supply responded actively to both the inflation rate and the real output and had certain effects on futures inflation rates and real output. Official interest rates, however, responded passively to the inflation rate and did not respond to the real output; they also do not have any effect on futures inflation rates and real output. Moreover, it could be learned from chapter 2 that the monetary growth channel (mainly through the credit channel) plays a bigger role than the interest rate channel in promoting commodity prices in China. Therefore, I include the year-on-year monetary aggregate M2 in our set of regressors.

4.3.1.3 Indicator on the market sentiment

Vrugt, Bauer and Molenaar (2004) argued that stock market sentiment is usually seen as a predictor of future economic developments. They added the total returns of the S&P 500 to the database. In China, stock is also widely accepted as an asset class. Here, I add the month-on-month total return of the Shanghai Composite Stock Index to the variable set. In chapter 3, I find that movement in the Shanghai Futures Exchange (SHFE) market can directly guide movement in the LME market. Accordingly, the one-month-lagged metal futures return (in the London Metal Exchange (LME)) is incorporated here to check whether price discovery and guidance from the SHFE could potentially offer effective timing signals. Finally, I add the Chinese foreign exchange rate (month-on-month return on the Renminbi-US dollar exchange rate) to see whether the pace of Renminbi appreciation could have any impact on metal futures prices.

To sum up, the variables to be included in these three categories are listed in the

following table. All of the data used in this chapter are from the Wind system, a China-based financial database. The data used are stylized in month terms.

Insert table 4.2 here

Figure 4.1 show the cumulative return and summary statistics of the metal futures return for the sample period. No obvious pattern can be found in the futures return series. However, it appears that volatility is quite high, particularly for copper and zinc. This variability implies that there is a huge potential for adopting dynamic timing strategies.

Insert Figure 4.1 here

4.3.2 Methodology

In the spirit of Vrugt, Bauer and Molenaar (2004), I employ a dynamic modelling approach to predict the sign of the monthly returns of the three metal futures listed on the Shanghai Futures Exchange. Econometrically, this approach involves a recursive estimation procedure that allows for continuous permutations among the determinants in accordance with a predefined model selection criterion. Evidently, the advantage of this method is that all possible models can be constantly re-estimated and re-evaluated to reflect an investor's continuous search for the best approximation of the most suitable model based on available information. The purpose of conducting this computationally intensive procedure is to minimize possible ex-post data-mining biases, which are likely to exaggerate the practical significance of the empirical results.

During the in-sample period, I estimate parameters for these models using standard Ordinary Least Squares (OLS). Following this procedure, each model generates monthly signals during a 12-month training period. Choosing the appropriate length of the training period is, to some extent, arbitrary. On the one hand, the period should

be long enough so that I can evaluate the performance of the timing strategy; on the other hand, the period should not be so long that the estimated models become less relevant as time passes. Here, the period is set to 60 months. If the signal for commodities is positive, metal futures are purchased; if the signal is negative, metal futures are sold.

Then at the end of the training period, I rank all models by their realized information ratios. The strategy with the highest realized information ratio is used to forecast the sign of the next month's metal futures return. Finally, in the out-of-sample trading , futures on the metal futures market are bought or sold depending on the signal.

In detail, the procedure is as follows:

Step 1: Define a set of six predictive variables, described in the previous section. To ensure a more robust and parsimonious model specification, I adopt an idea from Pesaran and Timmermann (1995) and constrain the number of forecasting variables in the model within the range of [1, 5]: namely a minimum of 1 and a maximum of 5. In doing so, I will test 63 models.

Step 2: Using an OLS modelling approach of the form

$$y_t = \alpha + \beta_1 x_{1t} + \beta_2 x_{2t} + \dots + \beta_i x_{it}, 1 \leq i \leq 5 \quad 4.2$$

I estimate all possible variable combinations using a 60-month rolling model estimation window. To ensure the forward-looking nature of the variables and to account for delayed data availability, all financial variables and macroeconomic variables are lagged 1 month.

Step 3: Then, I select the “best suitable” model based on the performance of the strategy in a rolling 12-month out-of-sample training period subsequent to the in-sample estimation period using a predefined selection criterion. The use of a selection period that postdates the model estimation sample relates to the evidence of

Bossaerts and Hillion (1999), who failed to find sufficient out-of-sample predictability using in-sample selection criteria. The selection criterion chosen is consistent with the main purpose of my dynamic timing strategies: to maximize a switching portfolio's information ratio, defined as the ratio of the mean return to the standard deviation (IR). The IR criterion selects models for their performance, as measured by the information ratio during the out-of-sample training period.

I estimate and select models for 1-month forecast horizons without considering transaction costs. Having selected the best model via training by selecting the model with the highest IR ratio, I can then implement the timing strategy in a second-stage out-of-sample period, the trading period.

For copper and aluminium, the in-sample estimation period starts from 2005.1 and stretches to 2010.12, the in-sample model selection period starts from 2011.1 and stretches to 2011.12, while the trading period starts from 2012 and stretches to 2013.12. For zinc, however, the in-sample model selection period starts from 2007.3 due to the data availability concern. Zinc futures start to trade after 2007.4.

This procedure described above is repeated every month (see Figure 4.2) and generates a ranking of preferred “best suitable” models for every time period in the sample and the subsequent out-of-sample timing decisions. Models are thus dynamically re-estimated and re-selected every month, which is in accordance with investors continuously searching for the best model specification given the data available at that point in time. To measure the effectiveness of our timing strategy in the trading period, I compare the information ratio of the dynamic timing strategy with that of a pure “buy-and-hold” strategy.

Insert Figure 4.2 here

4.4 Empirical results

In Figure 4.3, I present the empirical results of both the “buy-and-hold” (BH) strategy and the timing strategy for the three metals, copper, aluminium and zinc. It can be seen that the timing strategy offers better return, a lower standard deviation and as a consequence, a higher information ratio for all three metal futures. The strategy works especially well for zinc futures. It has a recorded return of 2.53% (an excess return of 2.57%) and lowers the standard deviation by more than 1%, leading to a much better IR ratio.

Insert Figure 4.3 here

The hit ratio, defined as the percentage of correctly predicted signals, is above 50% for all three products, with copper 58.33%, aluminium 54.17% and zinc 91.67%. According to the Henriksson-Merton (1981) non-parametric market-timing test, the active strategy possesses significant timing skill at the 5%-level of significance. Clearly, the “buy-and-hold” strategy takes long positions 100% of the time, whereas the active strategy takes quite different positions. It takes approximately 30% long positions for copper and fewer than 10% long positions for aluminium. For zinc, it takes half long positions and half short positions.

In Figure 4.4, I present the cumulative returns for the “buy-and-hold” and timing strategies. Moreover, I also plot the corresponding positions of the timing strategies (long or short in the three metal commodities futures) over time. It can be found that for both copper and aluminium, short positions dominate overwhelmingly. For aluminium, a long position is only taken in 2 months. However, the position taken for zinc is rather balanced: half of the time, long positions are taken and the other half, short positions are taken. To some extent, this suggests that the factor’s inclusion in zinc works in a very flexible way.

For both copper and aluminium futures, there appears to be a learning period for the strategy. After roughly 6 months, the dynamic timing strategy tends to catch up and provide continuous better performance. For zinc futures, it appears to work from the very beginning and to beat the “buy-and-hold” strategy completely.

Insert Figure 4.4 here

4.4.1 Factor inclusion

A question that naturally arises is which variables are predominantly selected over time. Figure 4.5 plots factor inclusion over time. The figure shows that variable inclusion is not stable over time, demonstrating the necessity of dynamic timing.

For aluminium, the variable exchange rate and the lagged LME aluminium returns are included over the entire period. This indicates that domestic aluminium is highly correlated to the global market. Meanwhile, the monetary growth variable is included in the first seven months of 2012 and the last seven months of 2013. It is worth mentioning that the monetary condition was very tight in China during these two ranges, while the period in between was relatively stable and tranquil. This reflects the sensitivity of the aluminium price to monetary tightening. Moreover, I find that in the range of 2012.8-2013.5, the stock index variable is included. The stock market provided a moderate return given the relative stability in the monetary market during that period. Hence, the stock market can provide better guidance than the monetary variable during this tranquil time. Furthermore, I find that the industry variable is included in the range 2013.6 – 2013.12; in this period, monetary conditions were tight and the macroeconomy had lost its momentum, the demand for aluminium is particularly weak. There were concerns in the market that some large aluminium plants would shut down to cut the surplus supply. Such concerns surely would dampen the aluminium futures price.

For copper, the factor inclusion appears to be comparatively irregular and inconsistent. All the six variables have been included during the out-of-sample period. The exchange rate is included in 20 months, 83% of the entire period. This result indicates that domestic copper, similar to aluminium, is highly correlated to the global market. From 2012.8, it can be seen that if industrial growth is included, M2 is excluded; if M2 is included, industrial growth is excluded. Several reasons could explain this phenomena. When the monetary environment is rather loose, as in the range of 2012.8-2013.5, its impact on commodity futures is weak, which can be demonstrated by the fact that only 2 months have been included. It is likely that industrial growth or even the stock market has a bigger sway on copper's futures price in that period. However, when the monetary environment is tight, its impact grows much greater. Other factors appear to be irrelevant.

For zinc, only four of the six variables have been included. Monetary growth and the inflation variable are excluded. The lagged stock return index and lagged LME zinc return variable are included over the entire period, this result shows that the zinc futures price is quite speculative and highly influenced by global markets. Moreover, the foreign exchange rate is included continuously for 19 months. Last but not least, the industrial growth variable is added from 2013.8, indicating that a weaker macroeconomy also dampens the performance of zinc futures prices.

Insert Figure 4.5 here

4.4.2 Economic intuition

The issue that many portfolio managers might have with this approach is the lack of an economic rationale to support the econometric model due to its “dynamic” variable inclusion. Although the selected variables are possibly related to the business cycle,

monetary conditions and market sentiment, the dynamic modelling approach I adopt here may not perfectly fit economic theory. Based on previous empirical evidence or personal experience, a portfolio manager may, for example, wish to restrict the sign of the business cycle (monetary conditions or market sentiment variables in the model to be positive). It could then be argued that model specifications with counterintuitive signs, although optimal in a statistical sense, should then not be taken into full consideration. The thought behind this argument is that erroneous short-run dynamics are probably specific for the time period considered and may disappear as quickly as they appeared.

However, in this chapter, this concern does not pose a problem. On the one hand, there are no strict signs between the independent and dependent variables that I should try to impose. China is experiencing a rapid transition, and thus no stable and consistent relationship between these variables could hold. I just try to reveal the relationship rather than present a precedent idea. On the other hand, the sample period is not long enough. Further restrictions on the sign of the parameters may cause statistical insignificance.

4.5 Conclusion

Scholars have shown that commodities serve as a good diversifier in portfolio management. Meanwhile, it has also been found that a dynamic timing strategy can offer better performance than a mere “buy-and-hold” strategy. In this chapter, I aimed at forming an effective dynamic timing strategy for China’s commodity market with full consideration of the Chinese specific factors based on the findings from Chapters 2 and 3.

Specifically, I adopt Vrugt, Bauer and Molenaar’s (2004) dynamic modelling approach to predict the sign of the monthly returns of the three metal futures listed on Shanghai Futures Exchange: copper, aluminium and zinc. Following Vrugt, Bauer and

Molenaar (2004), the base set of explanatory variables is classified into three categories: 1) business cycle indicators; 2) monetary environment indicators; 3) indicators of market sentiment.

Econometrically, the approach involves a recursive estimation procedure that allows for continuous permutations among the determinants in accordance with a predefined model selection criterion. During the in-sample period, I estimate parameters for these models using standard Ordinary Least Squares (OLS). Following this procedure, each model generates monthly signals during a 12-month training period. Then, at the end of the training period, I rank all models by the realized information ratios. The strategy with the highest realized information ratio is used to forecast the sign of the next month's metal futures return. Finally, in the out-of-sample trading period, futures on the metal futures market are bought or sold dependent on the signal.

From the empirical results, it can be seen that all three of the metal futures record good performance, and zinc's performance is particularly impressive. The hit ratio, defined as the percentage of correctly predicted signals, is above 50% for all three products. The fact that the dynamic modelling approach can provide a better information ratio than the pure "buy-and-hold" strategy proves that a dynamic timing strategy can deliver better results. It can be found that factor inclusion does vary across the entire sample period for all three metals. Meanwhile, it is worth mentioning that any concern regarding economic intuition does not pose a problem.

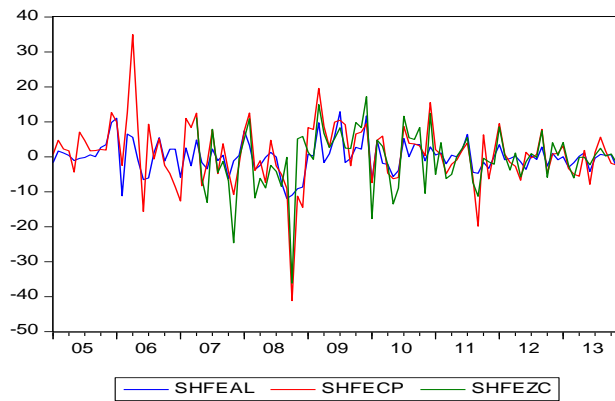
In this chapter, transaction costs have not been taken into account. It should be noted that transaction costs can be seen as incremental. Because futures have a finite life, a buy-and-hold strategy with futures also incurs transaction costs because the contract need to be rolled over. Timing strategies should suffer from higher transaction costs because they involve more frequent trading than the buy-and-hold strategy, with the information ratio lowered. However, incorporating a reasonable level of transaction cost will not fundamentally change the result because the excessive return delivered

by dynamic timing strategies is expected to fully cover those added costs compared to that of the buy-and-hold strategy.

Some lessons can be learned from the empirical results. First, factor inclusion can offer better performance: the implication is that in different stages, the effect of the same variable may be completely different. As is shown in the chapter, during the second half of 2013, the tight monetary environment is the primary focus, and a high interest rate lowers all asset prices including commodities and stocks; in other time ranges, when the monetary environment is moderately loose, the asset price is more influenced by other factors, such as the exchange rate and industrial growth. Therefore, practitioners such as asset managers should collect and analyse information on China's market accurately and carefully to determine which variable is the key indicator at different stages. Second, Chinese specific factors should be taken into consideration but should not be wildly exaggerated. From both chapters 2 and 4, it can be clearly seen that the monetary environment, measured by the money supply, has a major influence on China's asset price: to some extent, it does constitute a Chinese specific factor. Meanwhile, it can also be found under the same background of excess supply, that the futures price of aluminium is more influenced by domestic factors, while zinc is more influenced by global factors. Hence, Chinese specific factors should be treated with more objectivity.

Figures and Tables in Chapter 4

Figure 4.1: The descriptive statistics of the time series



Note: SHFEAL refers to the SHFE aluminium futures rate of return; SHFECP refers to the SHFE copper futures rate of return; SHFEZC refers to the SHFE zinc futures rate of return

Table 4.1 Descriptive statistics of time series

	INDUSTRY	CPI	M2	STOCK	USDCNY	LMECP_1	LMEAL_1	LMEZC_1	SHFECF	SHFEAL	SHFEZC
Mean	13.07	3.47	17.82	-0.02	0.29	0.44	-0.34	-0.28	0.00	-0.37	-0.48
Median	13.30	3.20	16.44	0.66	0.19	1.32	-0.77	0.14	0.71	-0.04	-0.01
Maximum	21.30	8.70	29.64	20.64	1.65	19.31	16.33	17.00	19.57	12.89	17.22
Minimum	5.40	-1.80	12.40	-24.63	-0.27	-34.87	-15.41	-32.14	-41.15	-11.90	-36.13
Std. Dev.	3.61	2.52	4.69	9.15	0.39	8.82	6.97	8.97	8.26	4.28	8.37
Skewness	0.10	-0.18	1.22	-0.41	1.15	-0.84	0.28	-0.53	-1.46	0.22	-1.14
Kurtosis	2.12	2.70	3.48	3.31	3.99	5.48	2.83	3.77	9.47	4.66	6.42
Jarque-Bera	2.68	0.73	20.49	2.60	20.77	29.97	1.15	5.64	168.22	9.83	56.48
Probability	0.26	0.69	0.00	0.27	0.00	0.00	0.56	0.06	0.00	0.01	0.00
Sum	1045.35	277.30	1425.31	-1.66	23.45	35.05	-27.32	-22.12	-0.24	-29.34	-38.32
Sum Sq. Dev.	1028.82	502.83	1739.20	6607.21	12.19	6141.27	3838.10	6360.36	5394.08	1445.18	5534.22

Note: SHFEAL refers to the SHFE aluminium futures rate of return; SHFECF refers to the SHFE copper futures rate of return; SHFEZC refers to the SHFE zinc futures rate of return; Industry refers to year-on-year industry production growth; CPI refers to the year-on-year rate of inflation; M2 refers to the year-on-year monetary aggregate; Stock refers to the month-on-month total return of the Shanghai Composite Stock Index; USDCNY refers to the month-on-month return on the Renminbi-US dollar exchange rate; LMEAL-1 refers to the one-month-lagged metal futures return for LME aluminium; LMECP-1 refers to the one-month-lagged metal futures return for LME copper; LMEZC-1 refers to the one-month-lagged metal futures return for LME zinc.

Figure 4.2: graphical presentation of the dynamic timing approach

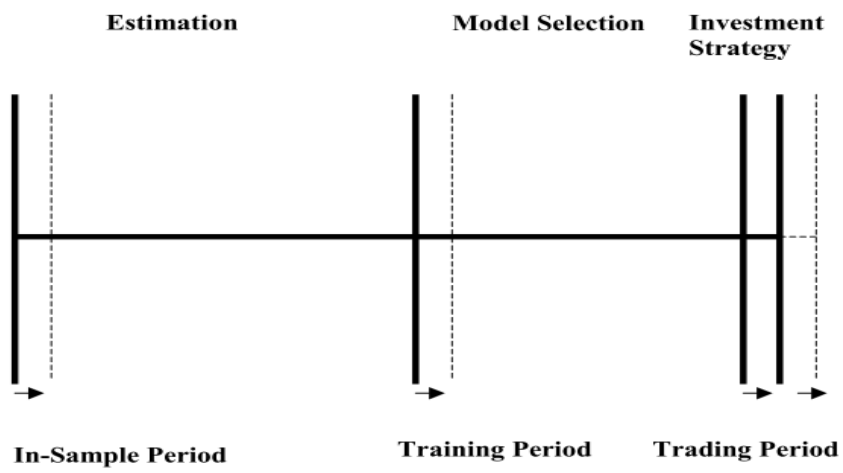


Figure 4.3: performance statistics for buy-and-hold and dynamic timing strategies

This figure shows the performance statistics for the “buy-and-hold” strategy and the commodity dynamic timing strategy. Signals are from the optimal model in the training period. This training period consists of 12 months, whereas the estimation period is 60 months

	Copper		Aluminum		Zinc	
	Timing	BH	Timing	BH	Timing	BH
average %	0.49	-0.15	0.58	-0.49	2.53	-0.04
std %	4.31	4.34	1.83	1.86	2.61	3.67
information ratio	0.11	-0.03	0.32	-0.26	0.97	-0.01
median %	0.88	0.71	0.45	-0.19	1.86	0.03
minimum %	-9.50	-7.85	-3.44	-4.21	-0.89	-6.06
maximum %	7.85	9.50	4.21	3.44	8.58	8.58
hit ratio	58.33%		54.17%		91.67%	
months long	7	24	2	24	12	24
months short	17	0	22	0	12	0

Figure 4.4: Cumulative performance of the buy-and-hold strategy and the dynamic timing strategies

The figures on the left show the cumulative excess returns for the buy-and-hold strategy and the dynamic timing strategy. The figures on the right provide the aggregate positions of the active strategy taken in the futures positions: 1 represents taking the long position, while -1 is taking the short position.

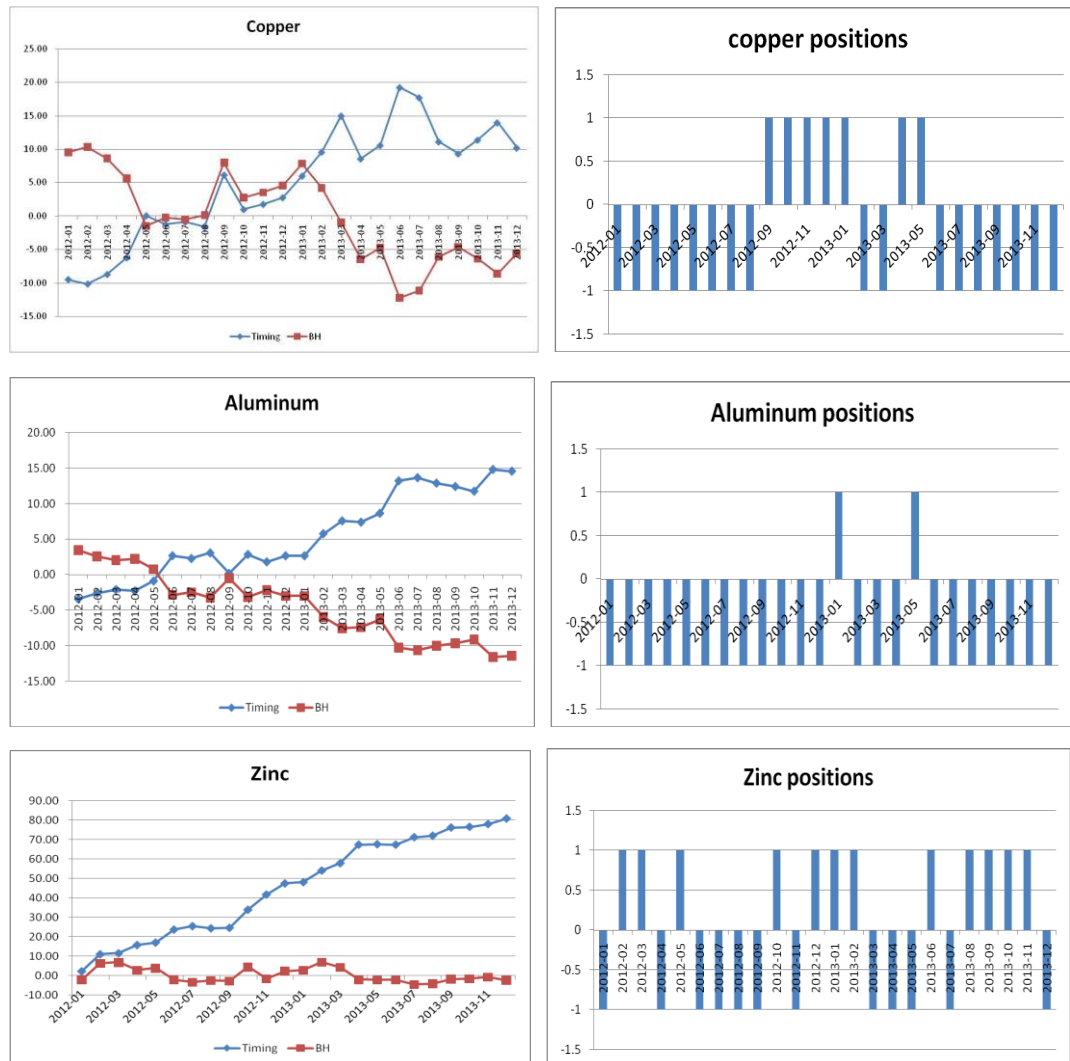
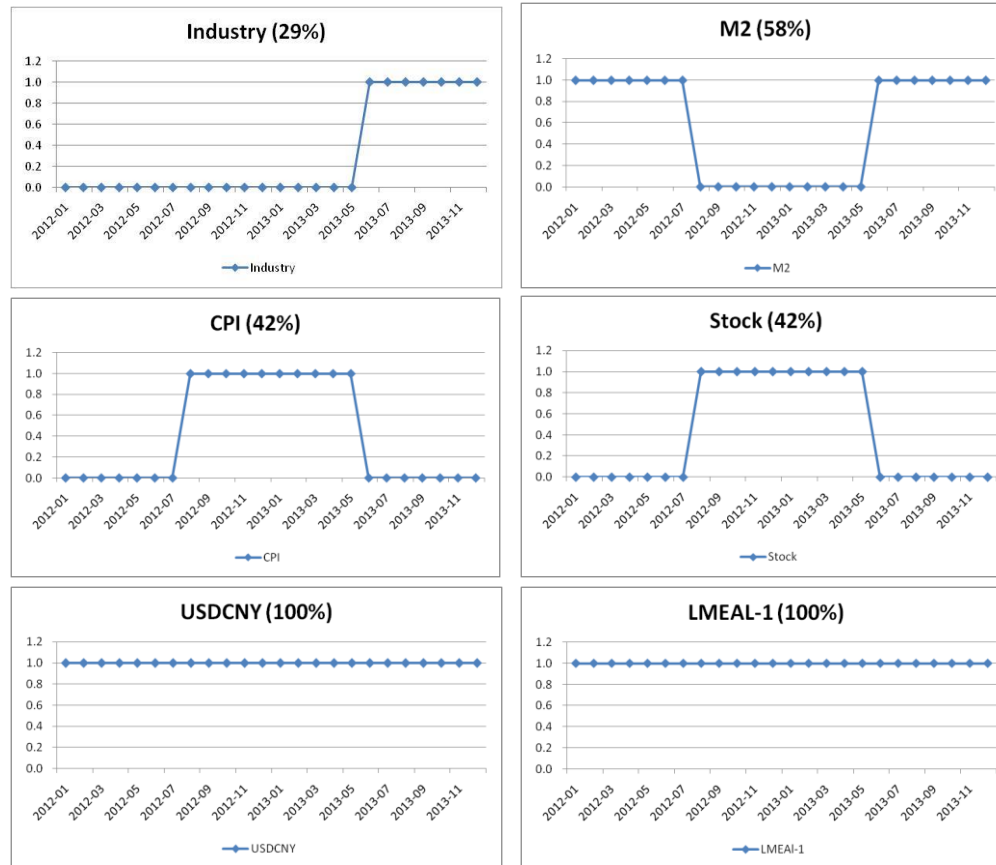


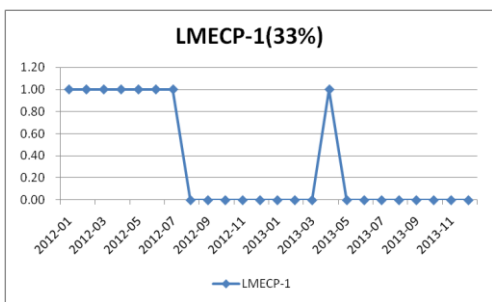
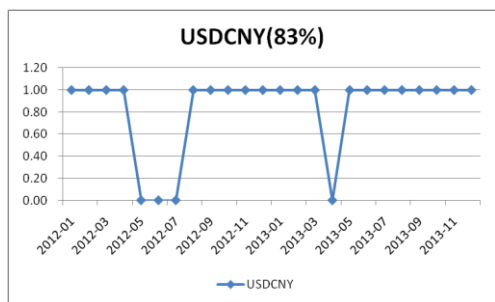
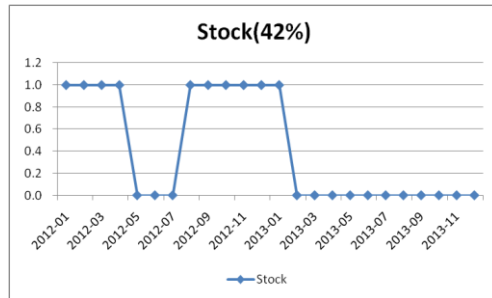
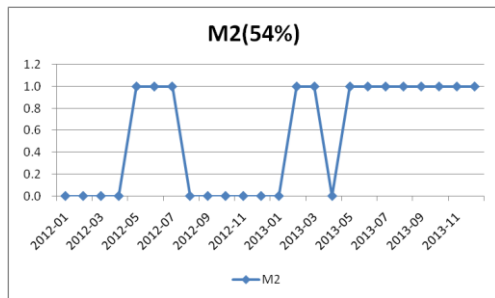
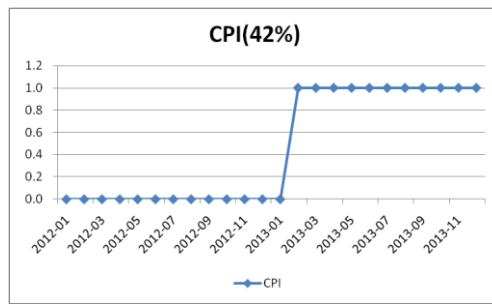
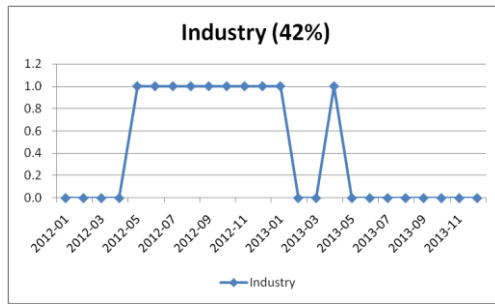
Figure 4.5 Factor Inclusion over Time

This figure presents the inclusion in the optimal model of the 6 factors in every time period for the three metal futures. Total inclusion in percentages is noted in parentheses.

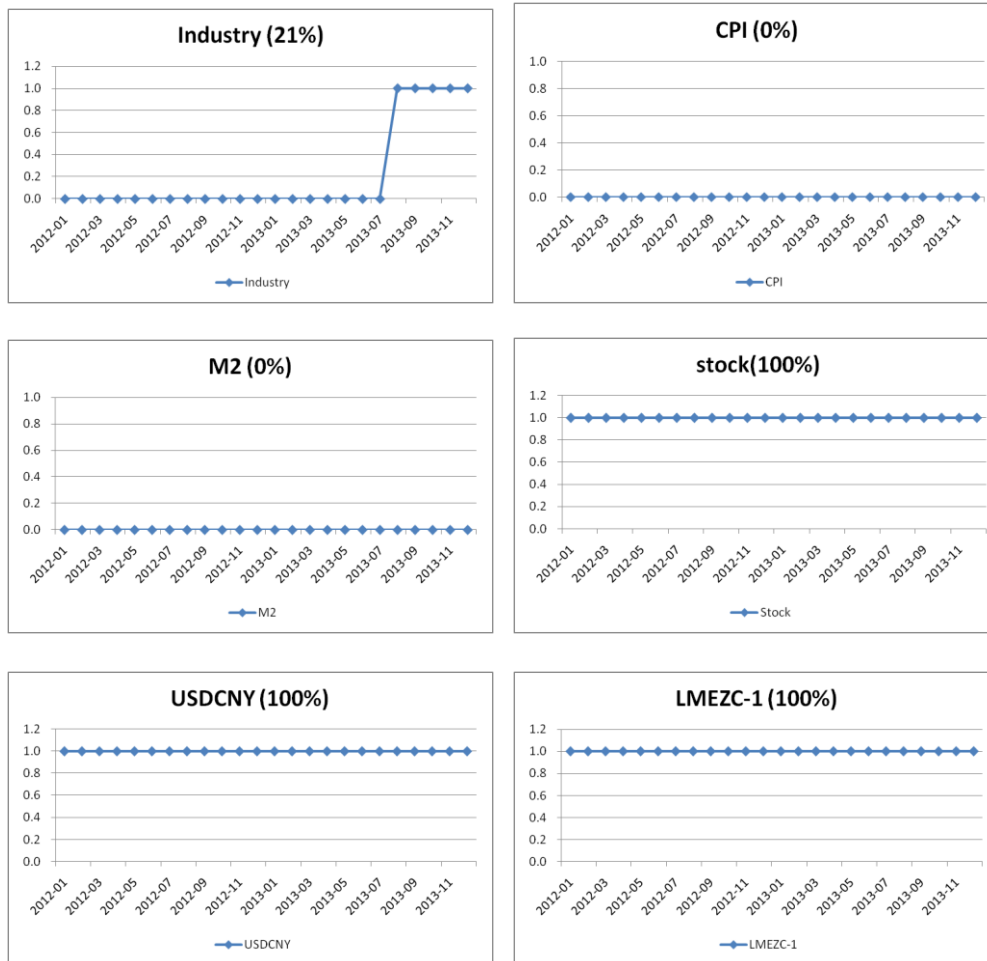
Aluminium



Copper



Zinc



Note: Industry refers to year-on-year industry production growth; CPI refers to the year-on-year rate of inflation; M2 refers to the year-on-year monetary aggregate; Stock refers to the month-on-month total return of the Shanghai Composite Stock Index; USDCNY refers to the month-on-month return on the Renminbi-US dollar exchange rate; LMEAL-1 refers to the one-month-lagged metal futures return for LME aluminium; LMECP-1 refers to the one-month-lagged metal futures return for LME copper; LMEZC-1 refers to the one-month-lagged metal futures return for LME zinc.

Table 4.2 Indicator categories and variable specification

Indicator category	Specific variables included
Business cycle indicators	Production: year-on-year industry production
Monetary environment indicators	Inflation: the year-on-year rate of inflation Money supply: year-on-year monetary aggregate M2
Indicators of market sentiment	Stock return: month-on-month total return of the Shanghai Composite Stock Index LME: one-month-lagged metal futures return Exchange rate: month-on-month return on the Renminbi-US dollar exchange rate

Chapter 5 Conclusions, implications and limitations

5.1 Conclusions

This study focuses on commodity futures investment considering the impact of Chinese specific factors. In chapter 2, I apply the overshooting model to investigate the empirical relationship between commodity prices and macroeconomic variables; in chapter 3, I explore the impact that China's futures market and the overseas futures market have on each other by investigating the information and risk spillover effects; moreover, I also examine China's pricing power in the global commodity futures market; then in chapter 4, I propose a dynamic timing strategy based on the understanding of Chinese specific factors developed in the previous two chapters.

Evidence from the SVAR models show that part of the theory of the relationship between macroeconomic variables and commodity price movement can be clearly supported. A negative relationship between interest rates and commodity prices can be demonstrated only for zinc, while positive "overshooting" between the interest rate and commodity prices, so-called "shock dependence," has been observed between the inter-bank repo rate and aluminium (copper) prices as well as between the exchange repo rate (average rate) and bean prices. As expected, a positive relationship between monetary growth and commodity prices can be demonstrated for several commodities with statistical significance. This shows that the monetary growth (credit) channel plays a bigger role than the interest rate channel in promoting commodity prices in China.

In chapter 2, I find that a sudden shock in the foreign exchange market prompts positive responses in some commodity prices. However, it might be more appropriate to consider that the foreign exchange rate plays a minor role in commodity price movement because the foreign exchange rate's movement is unidirectional.

Meanwhile, it can be found that shocks in output can lead to dramatic responses in some commodity prices.

Forecast error variance decompositions (FEVD) have been used to investigate the contributions of different structural shocks to fluctuations in the modelled variables. The empirical results suggest that the commodity price shock itself make the biggest contribution to commodity price shocks generally. An interest rate shock barely makes a contribution, while M1 growth shocks contribute much to metals shocks. Foreign exchange rate shocks provide a 40 percent contribution to some commodities. Industrial output shocks provide 20 to 30 percent contributions to some metals.

In Chapter 3, it can be seen that asymmetry factors are significant in both China's and the overseas futures market. In the Chinese metal futures market, the sign of the asymmetry factor is positive for copper and zinc futures while negative for aluminium futures. Therefore, although the mechanism of buying and selling is symmetrical in the futures market, the impacts of good news and bad news on market volatility are still asymmetric. For copper and zinc futures, the impact of bad news is greater; for aluminium, the impact of good news is greater. In the Chinese futures market, people prefer to take long positions in speculative copper and zinc products for psychological reasons (Liu, Cheng, Wang, Hong and Li, 2008). When the futures price goes up, the number of speculators also grows. With risk increasing, the reaction to market uncertainty consequently becomes stronger. As for aluminium, excessive supply has dampened its price over a long period of time. It is probable that any good news could lead to a moderate rebound in price. The sign of the asymmetry factor is different in the LME market, however. It is positive only for the copper product and negative for both aluminium and zinc products. The results show that the impacts of good news and bad news on market volatility are also asymmetric. A closer watch show that the sign of the asymmetry factor is identical for both aluminium and copper in the SHFE and the LME. Meanwhile, it can be seen that asymmetry factors are significant in the AUDUSD time series, and the sign of the factor is positive, indicating that the impact

of bad news is greater than that of good news for AUDUSD.

The empirical results for the Granger causality test in Chapter 3 support some of my proposed hypotheses. Specifically, the results indicate that in China's domestic market, futures pricing functions quite well because a two-way causal link is found between spot and futures products, indicating that the function of price discovery performs effectively and reliably in China. As for the interaction between the domestic and overseas futures markets, a causal link does exist from the SHFE market to the LME market; these results also hold for the extreme upside and downside scenario. To some extent, they show that the movement in the SHFE market can directly guide the movement in the LME market, indicating the increase in China's pricing power in commodities. As for the interaction between the SHFE metal market and the overseas financial market, no consistent conclusions have yet been found, indicating that the Chinese factor may have a limited impact on the global market as a whole.

The empirical evidence in chapter 4 suggests that the timing strategy could offer a better return, a lower standard deviation and, as a consequence, a higher information ratio for all three metal futures. The strategy works particularly well for zinc futures, in which case, it has a recorded return of 2.53% (an excess return of 2.57%) and lowers the standard deviation by more than 1%, leading to a much better IR ratio. The hit ratio, defined as the percentage of correctly predicted signals, is above 50% for all three products. According to the Henriksson-Merton (1981) non-parametric market-timing test, the active strategy possesses significant timing skill at the 5% level of significance. Clearly, the "buy-and-hold" strategy takes long positions 100% of the time, whereas the active strategy takes quite different positions. The active strategy takes approximately 30% long positions for copper and fewer than 10% long positions for aluminium. For zinc, it happens to take half long positions and half short positions.

In Chapter 4, the results also indicate that the factor inclusion does vary across the entire sample period for all three metals. For aluminium, the variable exchange rate and the lagged LME aluminium returns are included over the entire period. The results indicate that domestic aluminium is highly correlated with the global market. For copper, the factor inclusion appears to be comparatively irregular and inconsistent. All six variables were included during the out-of-sample period. For zinc, only four of the six variables were included, as monetary growth and the inflation variable are excluded. The lagged stock return index and the lagged LME zinc return variable are included over the entire period, showing that the zinc futures price is quite speculative and highly influenced by global markets. Furthermore, concerns about economic intuition do not pose a problem.

5.2 Implications

The results of this study provide implications for both researchers and commodity futures practitioners. Systematic research on Chinese specific factors suggests that these factors should be treated fairly. On the one hand, it can be said that Chinese specific factors do exist. A typical example is the monetary supply variable. From both chapters 2 and 4, it is clear that the monetary environment, measured by the money supply, has a large influence on China's asset price. Unlike developed countries, interest rate marketization in China is still in progress, and the pricing mechanisms for the interest rate need to be further improved. Consequently, monetary policy is mainly transmitted through the quantitative channel and not the price channel. On the other hand, I must emphasize that Chinese specific factors should not be wildly exaggerated. In chapter 4, under the same background of excess supply, results show that the futures price of aluminium is more influenced by domestic factors, while zinc is more influenced by global factors. Hence, the Chinese specific factors should be treated with objectivity.

This study can also offer investment specialists and portfolio managers insights and guidance for futures investment. First, the investigation into the relationship between futures prices and macroeconomic variables offers clear insights for investment specialists, who can add indicators such as monetary growth and industrial growth into their investment calendar. Prior to the announcement of these data, they can consider their expectation of the data to decide what positions to take. With the rapid pace of interest rate liberalization in China, changes in the interest rates of different markets should also be given increasing attention because it is likely that the price channel will have a growing impact on commodity prices.

Second, the study on China's pricing power over global commodities also carries weight. To some extent, the results in chapter 3 have demonstrated that China's commodity pricing power has grown stronger. Considering their expectations for domestic price movement and their judgment regarding the direction of information flow, portfolio managers could hold overseas commodity positions to conduct cross-market arbitrage. However, the strengthened pricing power is mainly reflected in the commodity market. Any extension to other capital markets might be quite risky.

Third, this study provides dynamic timing strategies for portfolio managers. Its simplified procedure and flexible factor inclusion offers them a better understanding for exploring investment opportunities. The implication is that in different stages, the effect of the same variable may be completely different. As shown in chapter 4, during the second half 2013, the tight monetary environment was the primary focus, and high interest rates brought all asset prices down, including commodities and stocks; in other time ranges, when the monetary environment is moderately loose, asset prices are more influenced by other factors, such as the exchange rate and industrial growth. Therefore, practitioners such as asset managers should collect and analyse information in China's market more accurately and delicately so that they can figure out which variable is the key indicator at different stages.

5.3 Limitation

The results have some limitations, and some interesting avenues are available for future research. In chapter 2, the empirical relationship has been checked between macroeconomic variables and all of the commodities. However, in Chapter 3, the information and risk spillover effect is mainly checked on metal futures because one key task is to detect whether pricing power has been strengthened in the metal market. Efforts could also be made in this area on agricultural futures to see whether any interesting conclusions can be reached.

In chapter 4, focus is mainly on dynamic timing strategies due to their simplicity, convenience and effectiveness. To incorporate the factors explored in Chapters 2 and 3 more thoroughly, other investment strategies should also be fully studied.

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